Diagnosis and Reconfiguration Planning With Resource Constraints

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Embedded, Collaborative Computing Area

Palo Alto Research Center

Worked performed at:

NASA Ames Research Center under 632 funding

Palo Alto Research Center

in collaboration with:

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Lee Brownston

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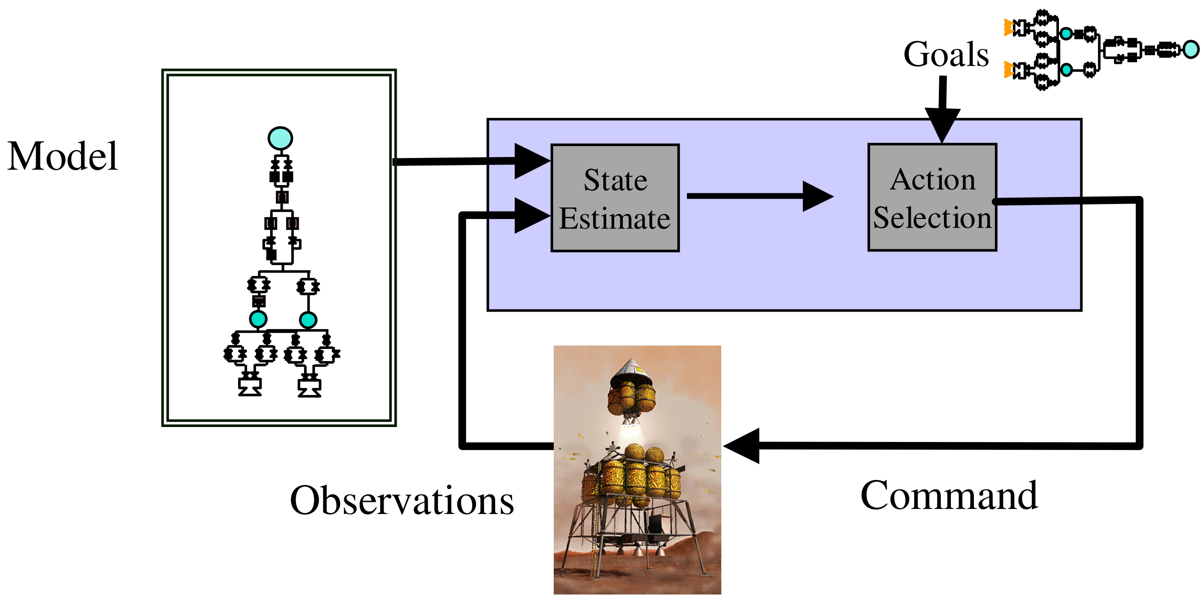
Problem Statement

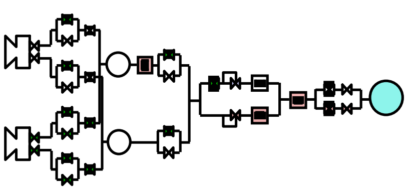
- Given
  - A model of a physical system such as a printer or spacecraft
  - The internal actions taken and observations received thus far
  - A description of the desired state of the system



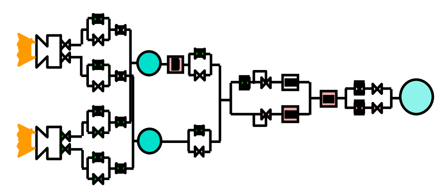
- Task
  - Determine the most likely internal states of the system
  - Find commands to move any likely state to a desirable state
  - If that’s not possible, do the best you can

Challenges

Initial State



Goal States



Time

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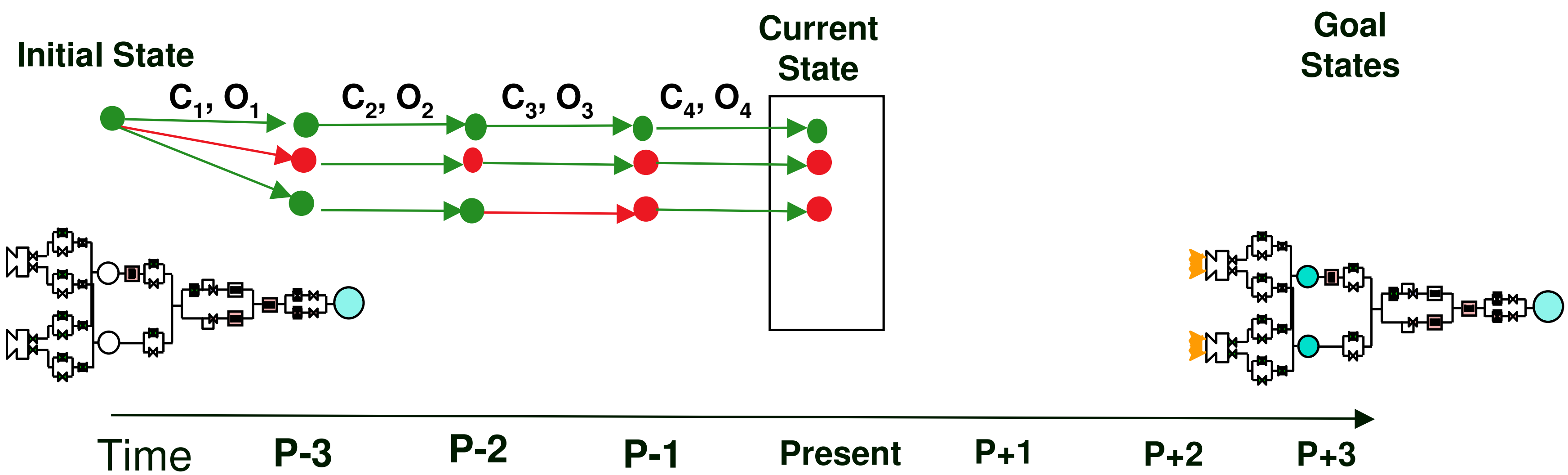
Challenges

- Diagnosis or State Estimation
  - **Definition:** After each command, determine the **set** of likely states
  - **Problem:** The state is not completely observable. The number of states is huge.
  - **Problem:** Failures may not manifest themselves at the time they occur.



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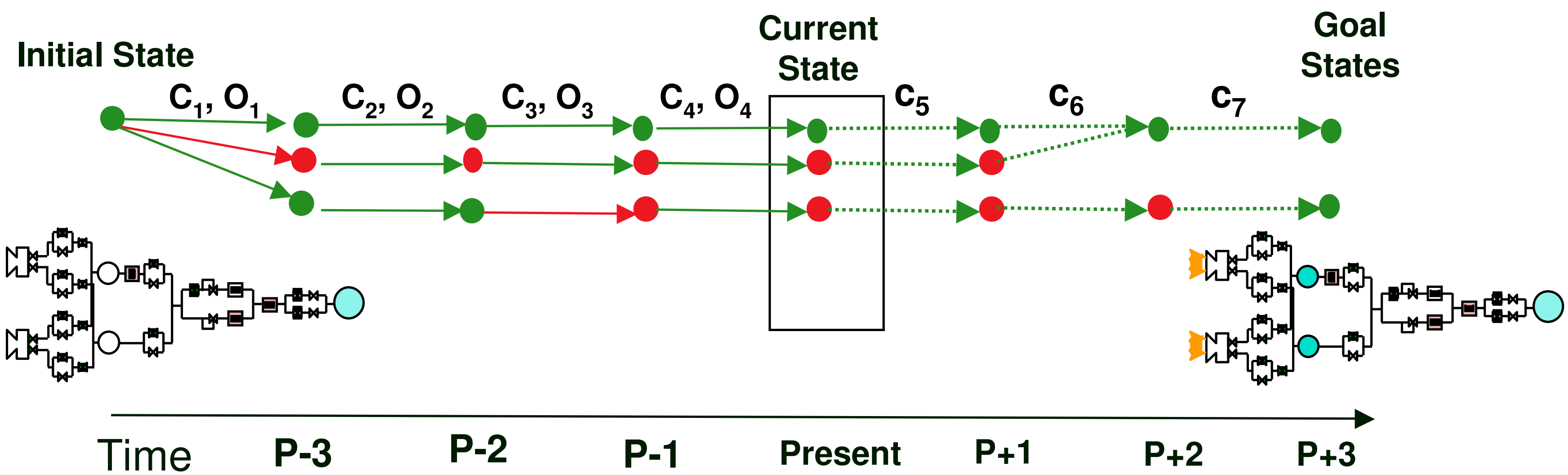
Challenges

- Conformant Planning
  - **Definition:** Given a set of states, find one plan that achieves the goal in every state
  - **Problem:** Actions chosen for one state can have unintended effects in another.



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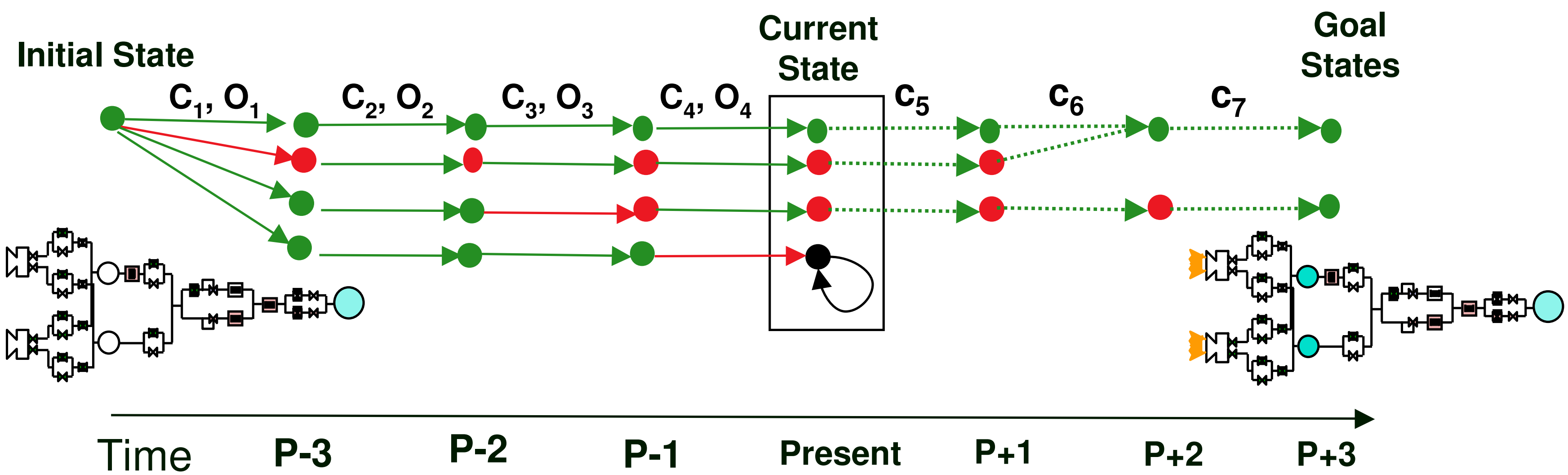
Challenges

- Planning With Failures
  - **Definition:** Plan to achieve as much as possible given failures and time limits
  - **Problem:** Every goal may not be achievable in every likely state.
  - **Problem:** Some combinations are much more difficult to plan for than others.



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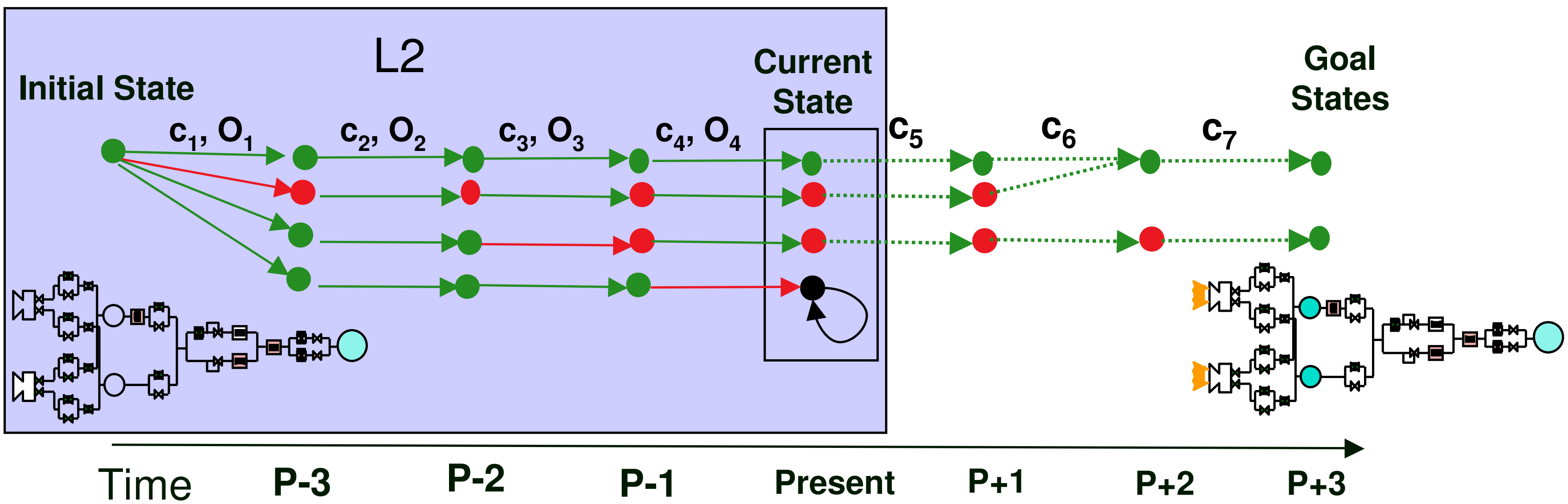
Status

- Diagnosis or State Estimation: L2 (Kurien & Nayak, AAAI 200)
  - Tracks multiple system trajectories
  - Backtracks to find failures that were not immediately observable
  - Extends ideas of Livingstone (Williams and Nayak, AAAI 1996) as flown on DS1
  - Used by S/C engineers to develop X-34, X-37 models & diagnostic scenarios
  - In use at NASA, licensed to a spacecraft software company
- Conformant Planning: fragPlan (Kurien, Nayak & Smith, AIPS 2002)
  - Novel, incremental approach to conformant planning
  - Operates in an anytime manner
  - Fastest conformant planner on problems with parallelism
  - Described in Kurien, Nayak and Smith, AIPS 2002
- Planning With Failures: SCOPE (in preparation)
  - Novel approach when desired plan is not possible
  - Demonstrates multiple strategies for reducing planning scope

Challenges



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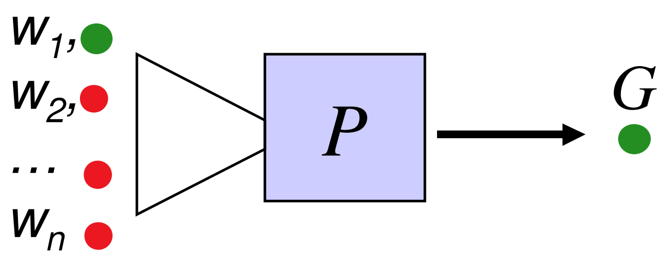
Conformant Planning

- Problem Instance
  - Let *Domain* be a description of a planning domain
  - Let *Worlds* be a set of initial states of the domain, $\{w_1, w_2, \ldots w_n\}$
  - Let *G* be a goal description
  - There are no sensing actions

- Task: Find plan *P* that applied to any w_i results in a state entailing *G*



- *P* is a conformant plan

- Challenge: Actions chosen in w_i may have undesirable effects in w_j

Existing Approaches to Conformant Planning

- Select actions for *P* by considering all *Worlds* simultaneously

CGP	Smith & Weld 1998	Graphplan over multiple plan graphs
CMBP	Cimatti & Roveri 1999	BDD representation of belief state
GPT	Bonet & Geffner 2001	Heuristic search in space of belief states
HSCP	Bertoli, Cimatti & Roveri 2001	BDD + heuristic search

- Generate a plan in w_i and test if it achieves *G* in all *Worlds*

CPlan	Castellini, Giunchiglia & Tachella 2001	SAT encoding determines possible plans which must be checked

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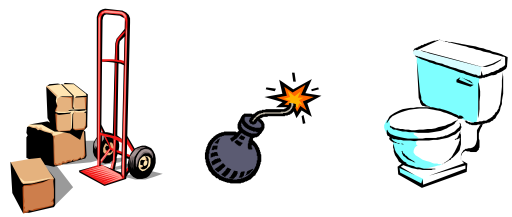
An Observation on Conformant Plans

- Example Domain: Bomb in the Toilet
  - Set of N packages, p1 through pN
  - Packages may have bombs (1, many, a subset)
  - Bombs defused by dunking the package in the toilet
  - The toilet must be flushed before dunking again



- Example Problem
  - 1 toilet
  - 6 packages
  - A bomb is in p1, p2, p3, p5 or (p4 & p6)

Bomb in the Toilet

6 packages, 1 toilet

Plan Step	Action
1	Dunk p3
2	Flush
3	Dunk p2
4	Flush
5	Dunk p1
6	Flush
7	Dunk p6
8	Flush
9	Dunk p4
10	Flush
11	Dunk p5

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- Fragment if bomb in p1

Bomb in the Toilet

6 packages, 1 toilet

Plan Step	Action
1	Dunk p3
2	Flush
3	Dunk p2
4	Flush
5	**Dunk p1**
6	Flush
7	Dunk p6
8	Flush
9	Dunk p4
10	Flush
11	Dunk p5

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- Fragment if bomb in p1

- Fragment if bombs in p6 and p4

Bomb in the Toilet

6 packages, 1 toilet

Plan Step	Action
1	Dunk p3
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3	Dunk p2
4	Flush
5	Dunk p1
6	Flush
7	Dunk p6
8	Flush
9	Dunk p4
10	Flush
11	Dunk p5

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- Fragment if bomb in p1 → steps 4–5
- Repair action to unify fragments → step 6
- Fragment if bombs in p6 and p4 → steps 8–9

Bomb in the Toilet

6 packages, 1 toilet

Plan Step	Action
1	Dunk p3
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4	Flush
5	Dunk p1
6	Flush
7	Dunk p6
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9	Dunk p4
10	Flush
11	Dunk p5

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- Every conformant plan P must contain a fragment that achieves the goal in each world

- Each world has plans that are fragments of some P

- Approach:

  Grow a set of fragments into a conformant plan

Bomb in the Toilet

6 packages, 1 toilet

Plan Step	Action
1	Dunk p3
2	Flush
3	Dunk p2
4	Flush
5	Dunk p1
6	Flush
7	Dunk p6
8	Flush
9	Dunk p4
10	Flush
11	Dunk p5

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Fragment-based Conformant Planning

- Intuition

For each w_i in *Worlds* {

1. Generate a plan for *Domain* to achieve G in w_i
2. Add the planned actions to *Domain*

}

- Step 2 ensures the plan for w_{i+1} includes the actions that achieved G in $\{w_1 \ldots w_i\}$

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Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1					
1	Dunk p1					
2						
3						
4						
5						

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Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1	Fragments for p2 plan				
1	Dunk p1	Dunk p1				
2						
3						
4						
5						

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Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1	Fragments for p2 plan	Plan for {p1,p2}			
1	Dunk p1	Dunk p1	Dunk p1			
2						
3			Flush			
4						
5			Dunk p2			

Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1	Fragments for p2 plan	Plan for {p1,p2}	Extracted fragment		
1	Dunk p1	Dunk p1	Dunk p1			
2						
3			Flush			
4						
5			Dunk p2	Dunk p2		

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Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1	Fragments for p2 plan	Plan for {p1,p2}	Extracted fragment	Fragments for p3 plan	
1	Dunk p1	Dunk p1	Dunk p1		Dunk p1	
2						
3			Flush			
4						
5			Dunk p2	Dunk p2	Dunk p2	

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Fragment-based Conformant Planning

Planning Process

Plan Step	Plan for p1	Fragments for p2 plan	Plan for {p1,p2}	Extracted fragment	Fragments for p3 plan	Plan for {p1,p2,p3}
1	Dunk p1	Dunk p1	Dunk p1		Dunk p1	Dunk p1
2						Flush
3			Flush			Dunk p3
4						Flush
5			Dunk p2	Dunk p2	Dunk p2	Dunk p2

- Search will be required
  - The fragment chosen for w1 may not allow a plan for w2
  - The fragment chosen for w2 may disrupt the plan for w1

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The FragPlan Algorithm

completed=$\emptyset$
While (*Worlds* $\neq \emptyset$) {
select and remove world w_i from *Worlds*
Choose a plan P_i for *Domain* that achieves G in w_i
Fail if P_i doesn't achieve G for all $w \in$ *completed*
Extract fragment F_i from P_i
Domain = *Domain* + F_i
add w_i to *completed* }
Return P_i

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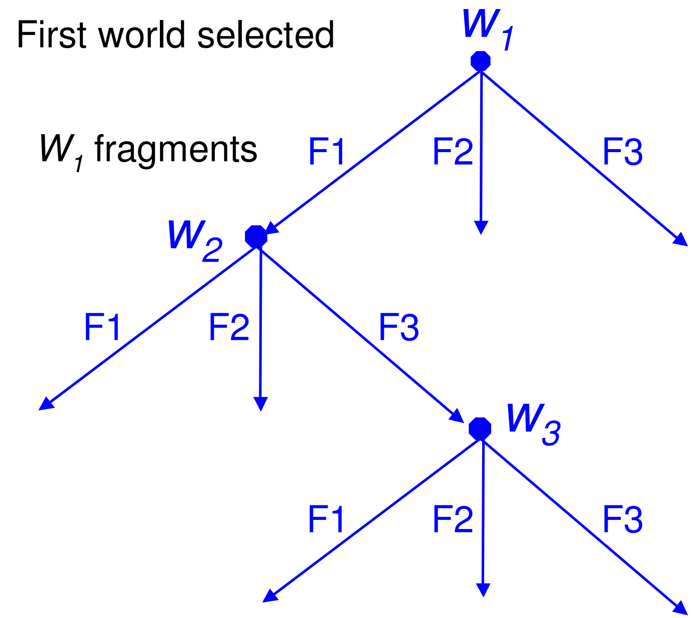
Search Strategies



- Chronological Backtracking
- Probing
  - Extend fragments to as many worlds as possible, then restart
  - On failure, discard all fragments and empty *completed*
  - Effective even when a small subset of worlds are very difficult
  - Fits well with deterministic planner we use to choose P_i for w_i
- Bubbling
  - Find difficult worlds. Solve first by moving them up the stack.

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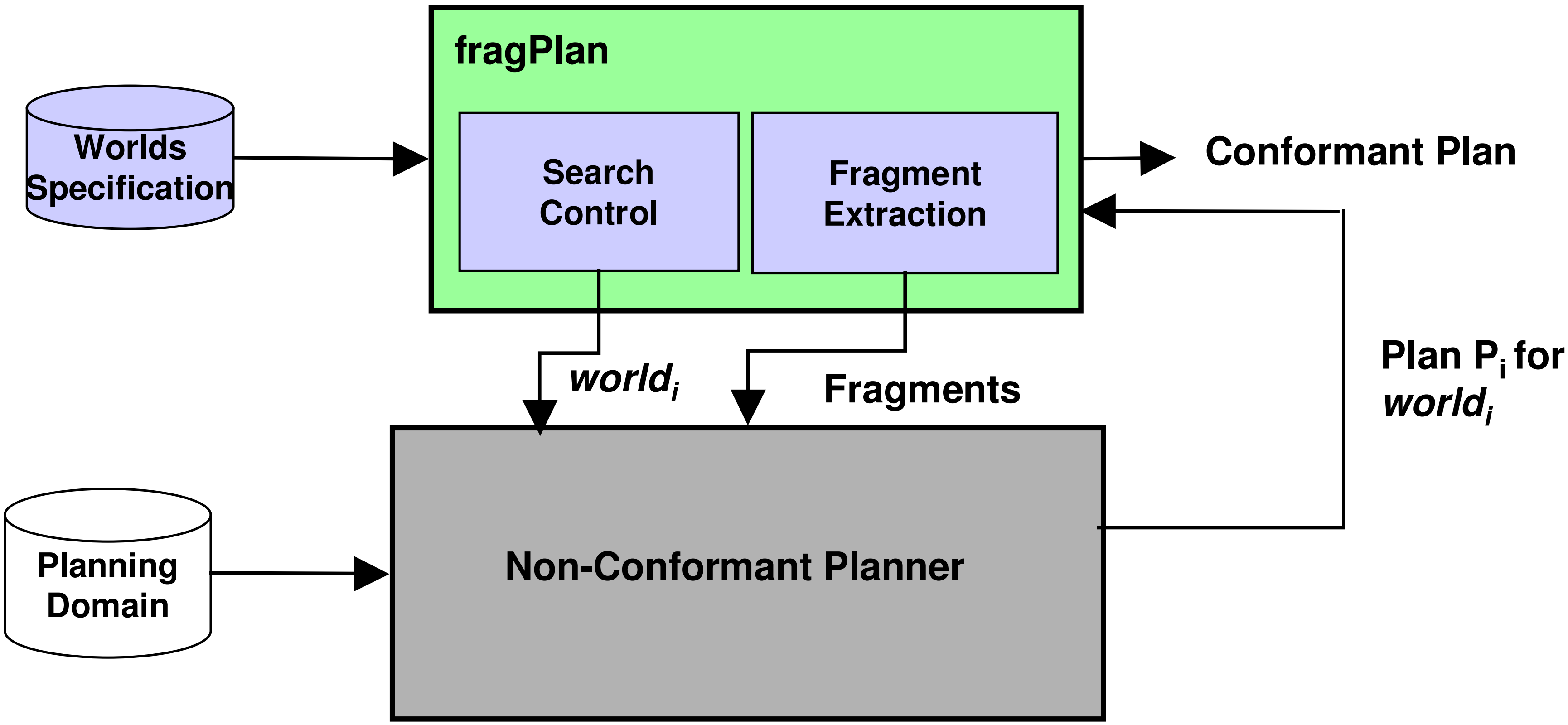
Implementation



- fragPlan uses a non-conformant planner as a black box
- We need only to be able to force the planner to include fragments

Domains Considered

- Hydraulic/Electric Networks
- Grid Worlds
  - A robot is in a ring of rooms
  - It must close and lock all windows
- Logistics
  - Packages must be delivered to various cities
  - Some roads have mines
- Bomb in the Toilet
  - A set of packages arrive, one or more has a bomb
  - Detailed results available for many planners
- Focused on problems solvable on a reactive (few seconds) scale
- World sets tested up to size 150, goal sets up to size 10

Unique Characteristics of fragPlan

- Novel algorithm for conformant planning that performs well on both serial and parallel problems
- Constructive approach
  - We always have a plan, improves in an anytime manner
  - Can delete and add worlds and re-use partial results
- More scalable than other possible worlds approaches
  - Memory usage is constant as the number of worlds increases
  - Computation is less susceptible to explosive growth

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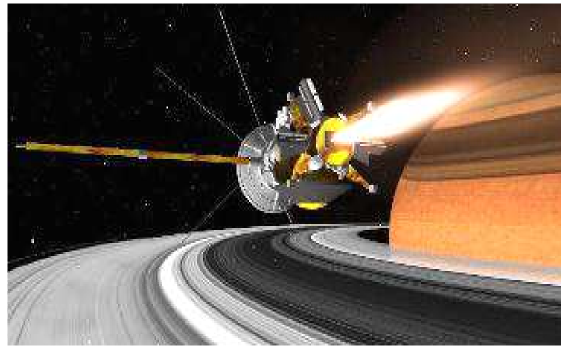
Is Conformant Planning Enough?



- Typical Goals
  - Configure the spacecraft to thrust to enter orbit
  - Configure the camera to take science images on approach

- Typical Safety Constraints
  - Turn the amp off before switching transponders to avoid burn out.
  - Once a device is on, never turn it off. It might not come back on.
  - I’m loathe to blow the pyro valves that enable the backup engine

- Typical Failures
  - The camera is dead, it’s power popped off, or its interface is hung
  - Thruster +x+y or –x-y is clogged

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SCOPE - Safe, Conformant, Optimizing Planning Engine

- Goal: Find the best possible plan in the available time
- Approach: Manipulate the scope of the problem

```
While (Time ≠ 0) {
    select constraints from {Worlds ∪ Goals ∪ Safety}
    FragPlan(constraints)
    }
```

- Challenge:
  – Which subsets of {*Worlds* $\cup$ *G* $\cup$ *S*} admit a plan?
  – Will we have a plan when time runs out?

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SCOPE – Safe, Conformant, Optimizing Planning Engine

- Approach: Manipulate the scope of the problem

While ($Time \neq 0$) {

select constraints from {$Worlds \cup Goals \cup Safety$}

FragPlan(constraints) for some time

}

Balance solving current constraints vs. exploration

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SCOPE – Safe, Conformant, Optimizing Planning Engine

- Approach: Manipulate the scope of the problem

While ($Time \neq 0$) {
    select constraints from {$Worlds \cup Goals \cup Safety$}
    FragPlan(constraints) for some time
    }

- Pareto-optimality requires checking all constraint subsets

- We have developed many simpler selection policies and experimented with several

Status

- Diagnosis or State Estimation: L2 (Kurien & Nayak, AAAI 200)
  - Tracks multiple system trajectories
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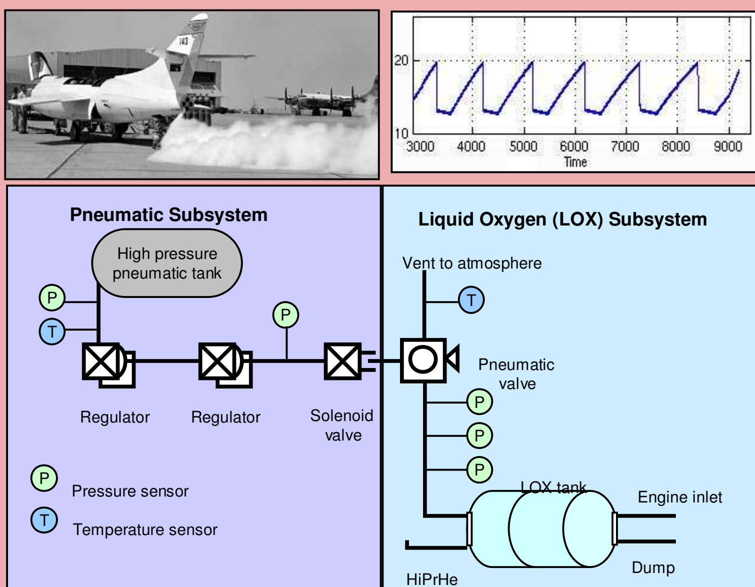
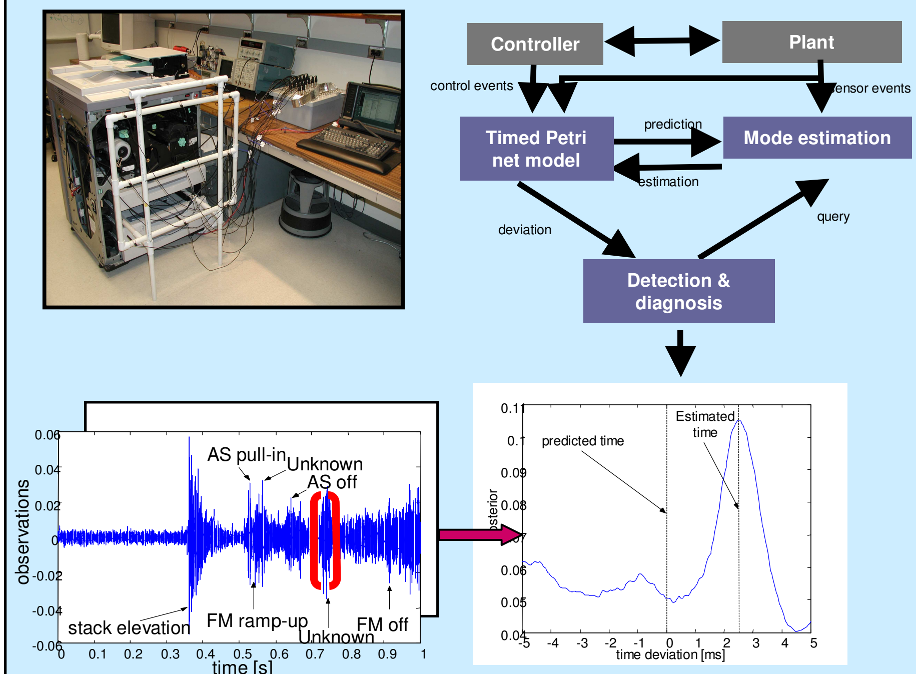
Some Current Work at PARC

Hybrid and Distributed Diagnosis



Diagnosis of Continuous Systems



Backing Slides

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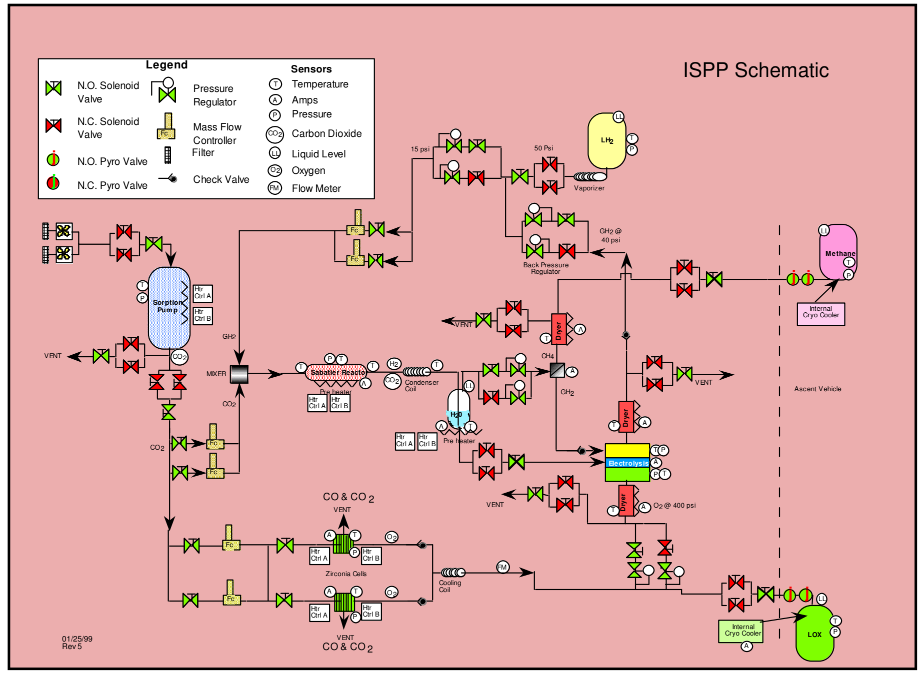
Cool Problems at NASA & PARC



- How do we make complex systems autonomous?
- How can they continue operating after failures?

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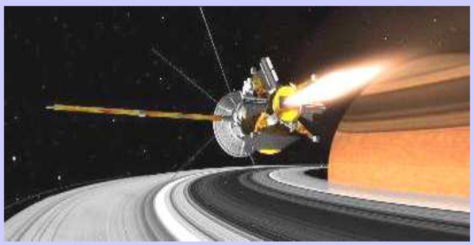
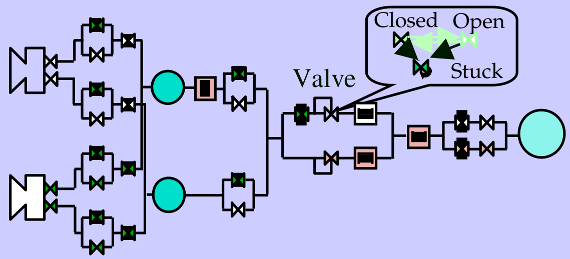
What is planning?

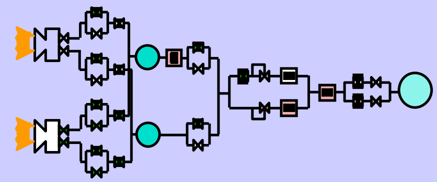
Typical Application	Domain Model	Typical Goal

Autonomous Machines

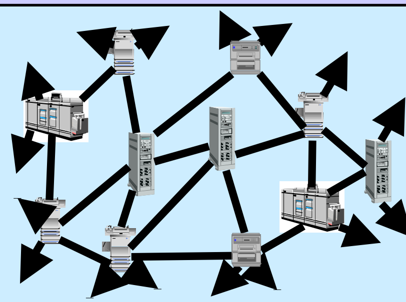




Configure the craft to thrust

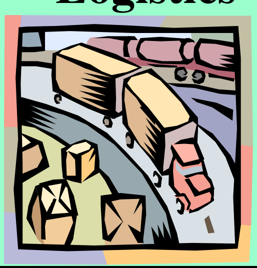


Web Software Agents



Buy me a cheap ticket to Rio during Carnival and print my itinerary at a printer near my office.

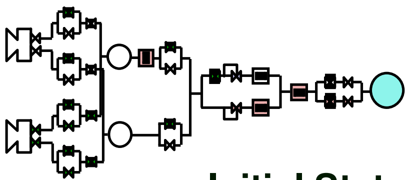
Logistics



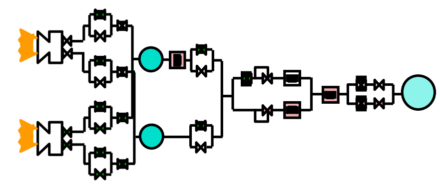
Deliver package A to San Jose, package B to Oakland, package C to Daly City ….

Choosing Actions

Action: Ignite Engine	
Pre:	Oxygen Flowing
	Fuel Flowing
Post:	Engine Thrusting



Initial State

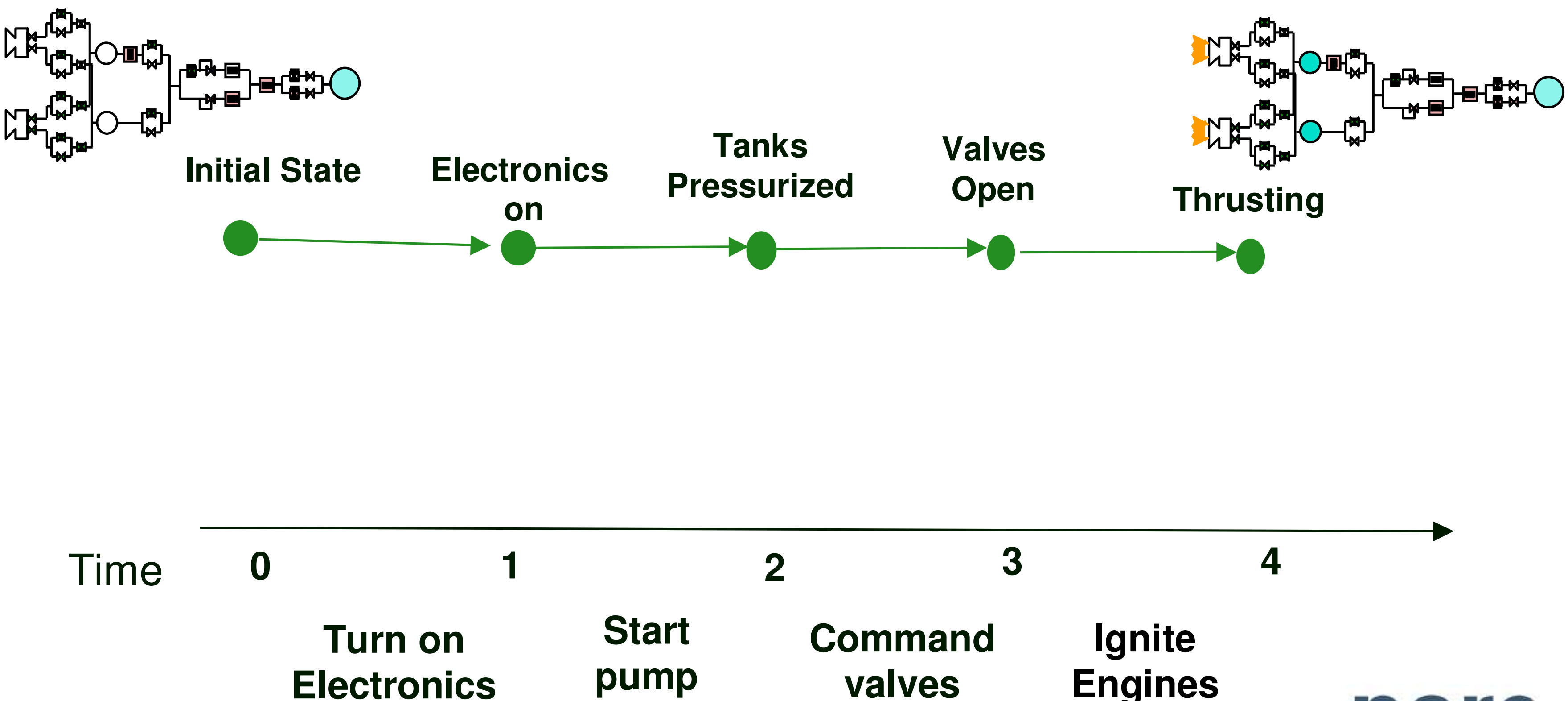


Thrusting

Time 0 1 2 3 4

Choosing Actions

Action: Ignite Engine	
Pre:	Oxygen Flowing
	Fuel Flowing
Post:	Engine Thrusting



Choosing Actions

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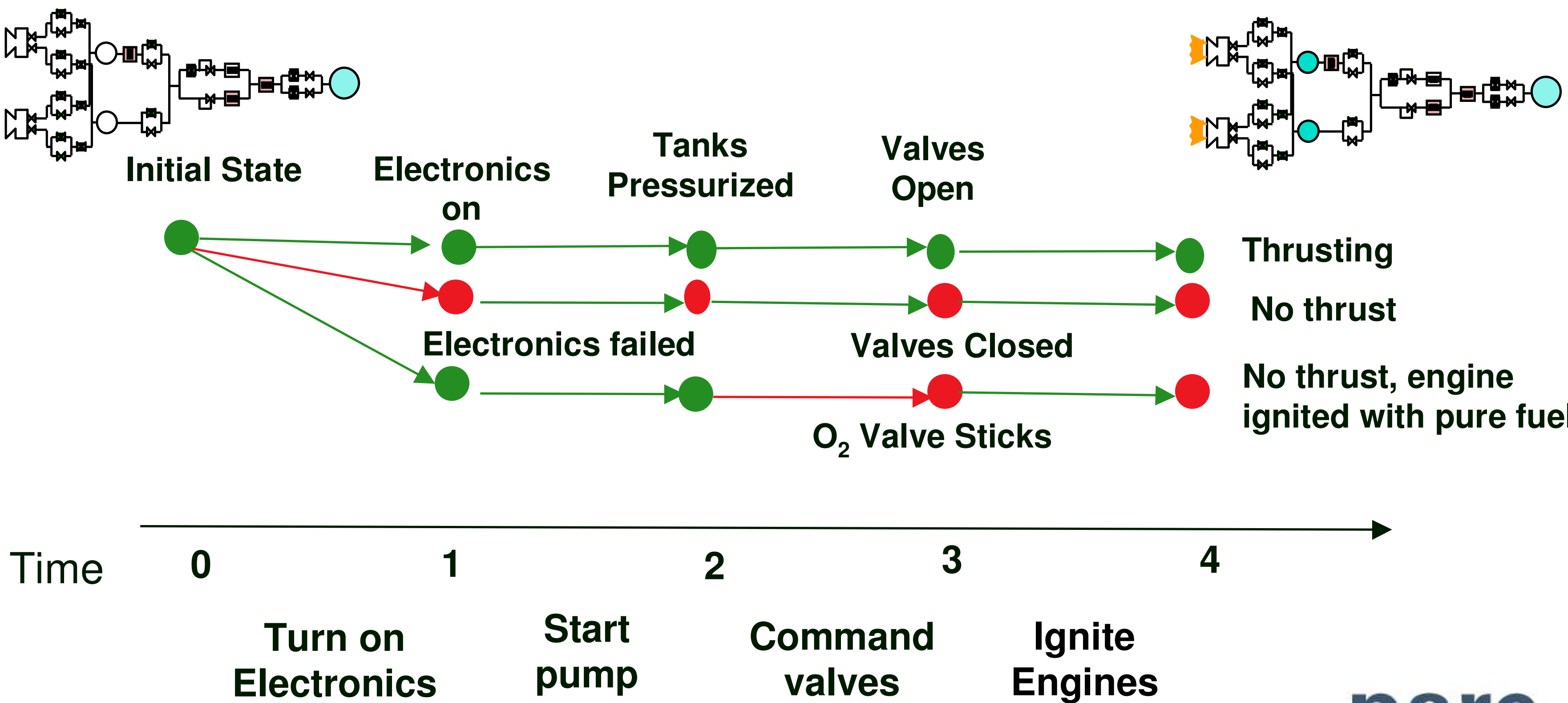
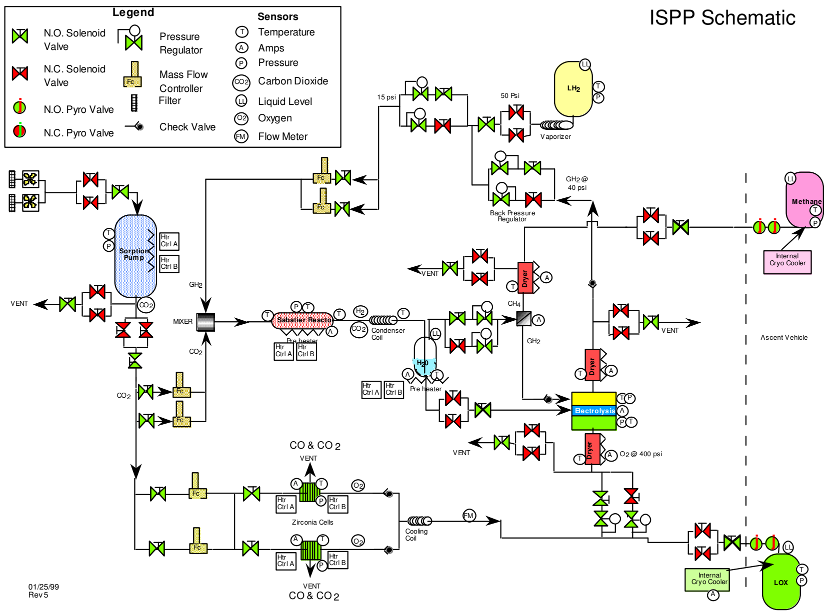
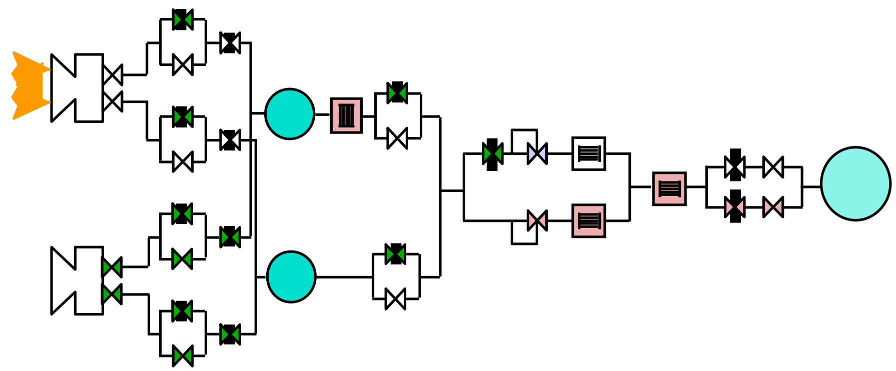


Our State Estimation Problems

Mars Propellant Production Model



Spacecraft Propulsion System Model



- Hundreds of variables
- Typically 10^{150} discrete states
- Mostly deterministic, but components will fail
- Failure probabilities known only by rank or order

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Approaches to State Estimation

- Exact methods
  - Problem: State space is enormous and discontinuous

Kalman filter	Kalman 1960	Continuous only, unimodal, white noise
Dynamic Bayes' net	Pearl 1988	Need to compute huge joint distributions

- Approximate the distribution over the state space
  - Problem: System is almost deterministic with abrupt failures

Approximate DBN	Boyen & Kohler 1998	Depends upon stochasticity assumptions
Particle Filters	Dearden 2002	Particles attracted to likely states

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Approaches to State Estimation

- Model-based diagnosis based upon logical consistency
  - Advantage: Compositional
    - Refuting a diagnosis of a component may refute an exponential number of system diagnoses (states)
  - Advantage: Incremental
    - Diagnoses (states) are generated in order of likelihood
  - Problem: Actions or evolution over time not handled well, or at all

Sherlock, GDE	De Kleer & Williams 1989	No actions or state evolution
Livingstone	Williams & Nayak 1996	State evolution, but arbitrarily bad approximation of the most likely state

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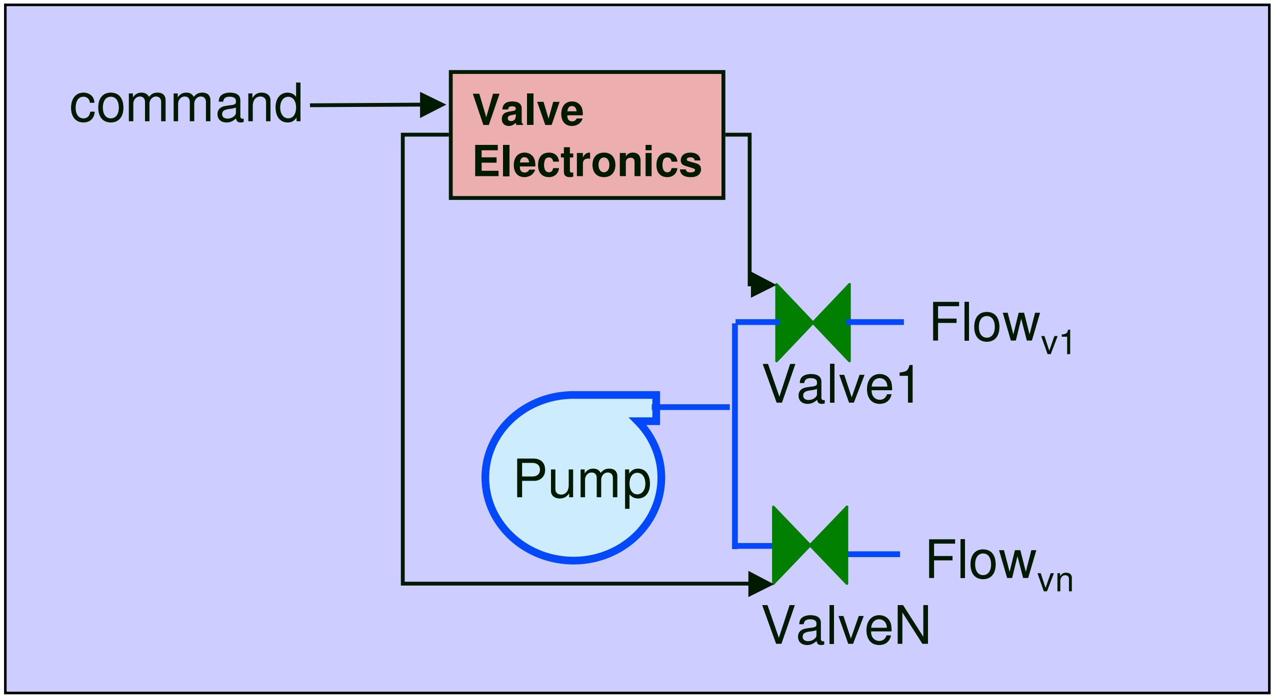
Simple Valve Example



- The pump pressurizes the valves
- Valve electronics send commands to valves
- Flow measured at each valve
- Electronics may hang, valves may stick shut

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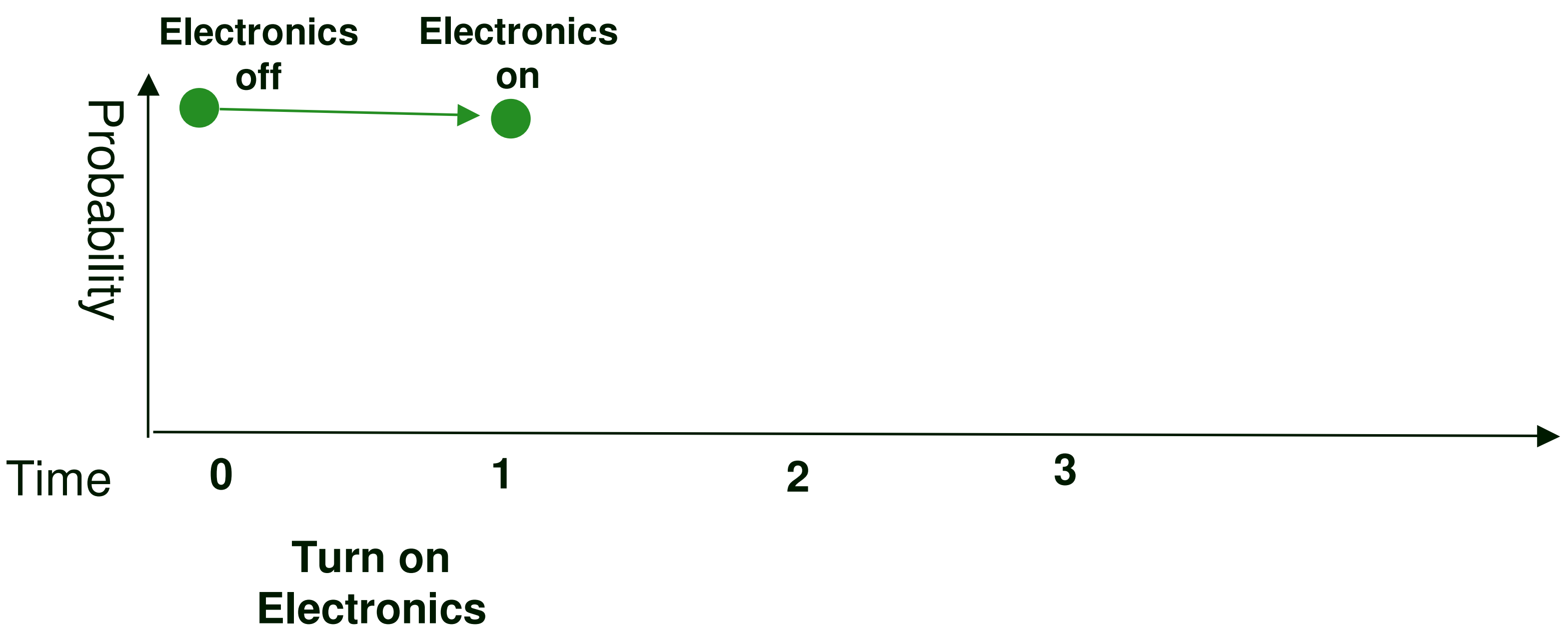
Traditional Diagnosis



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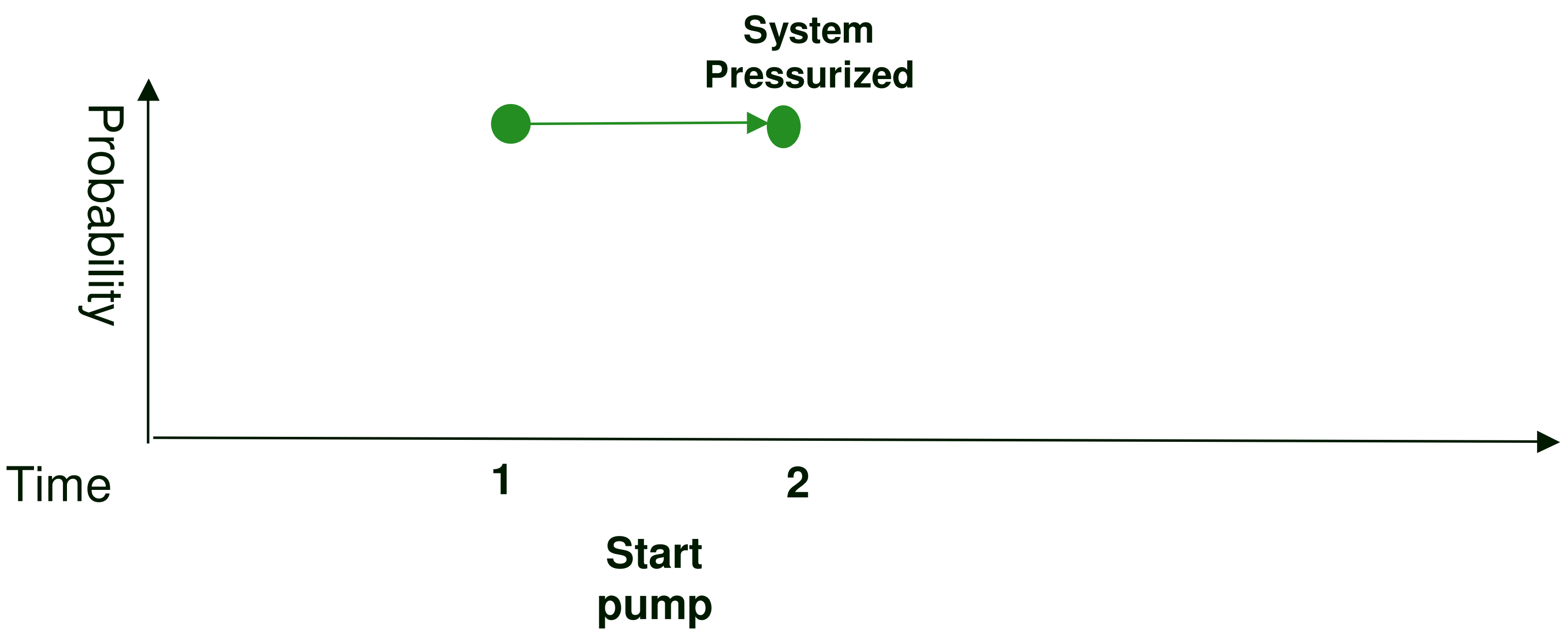

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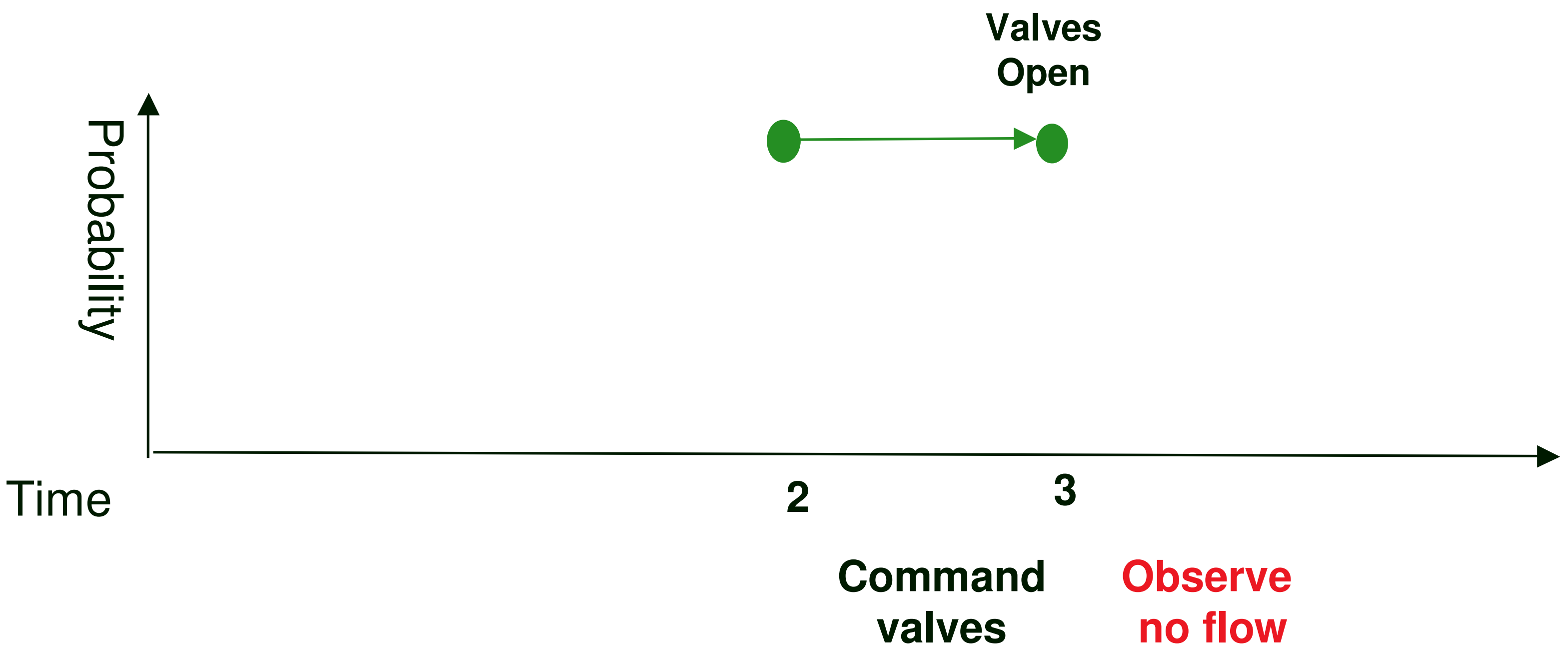

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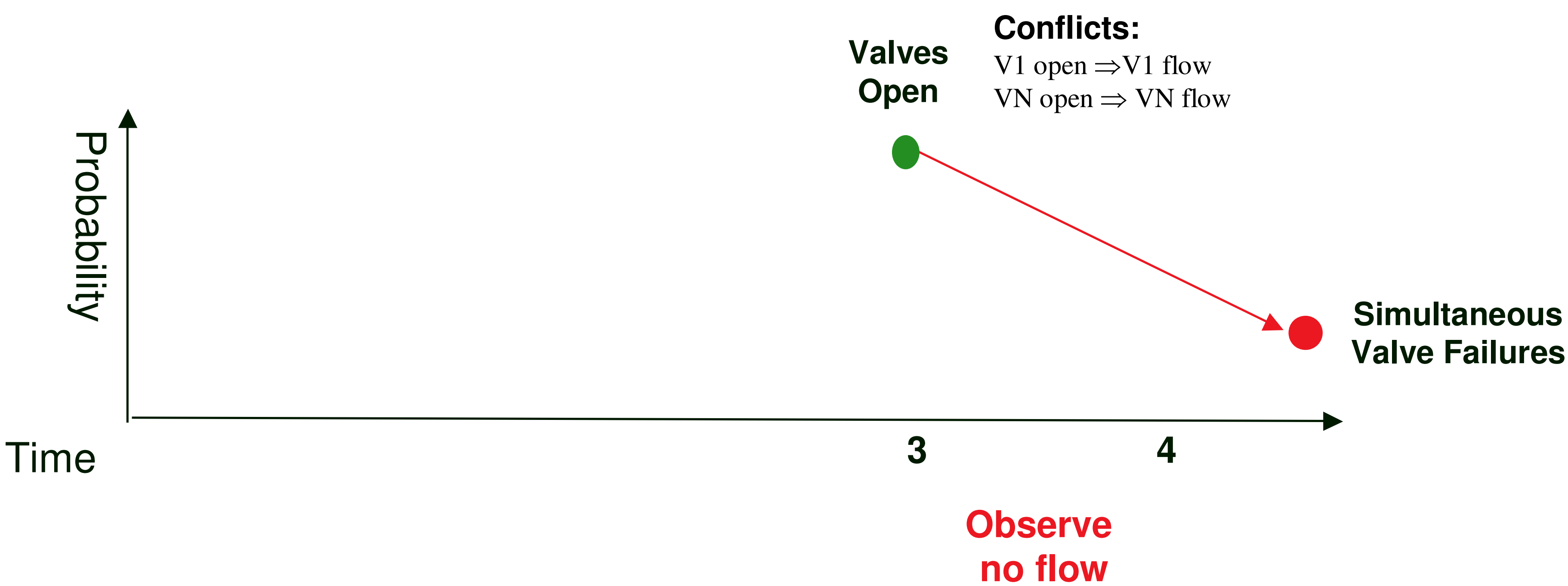
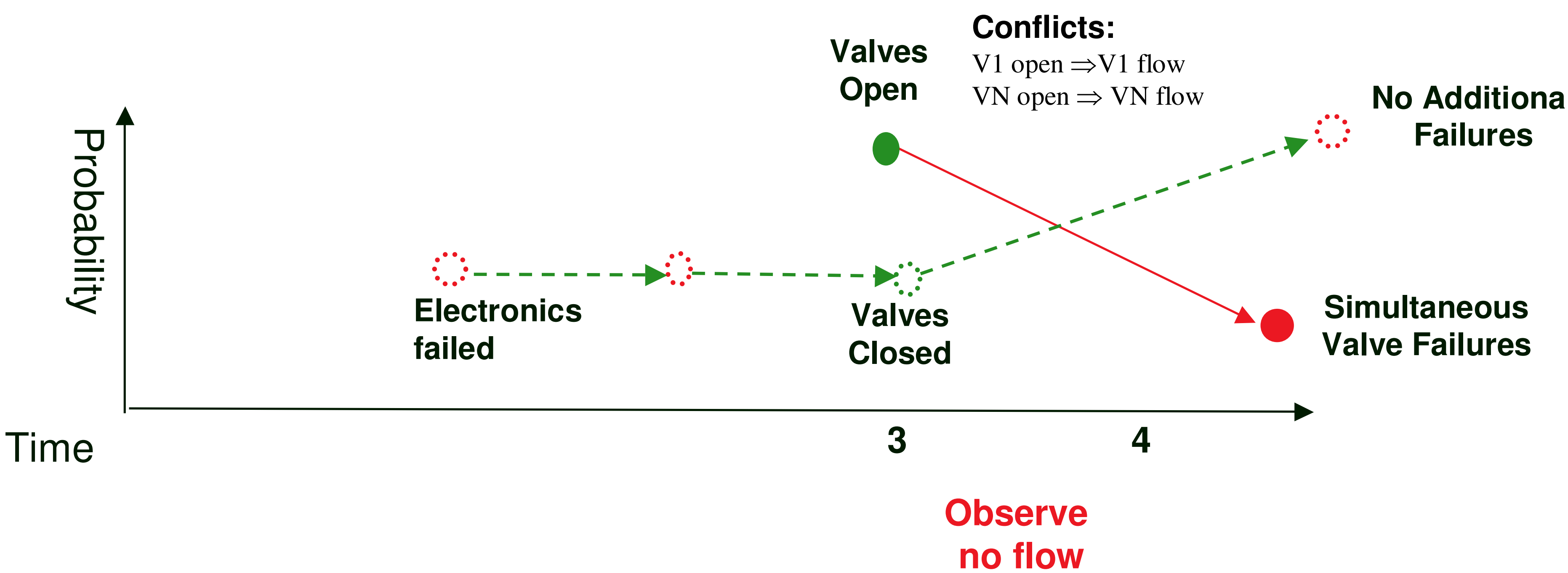
Traditional Diagnosis



The Problem



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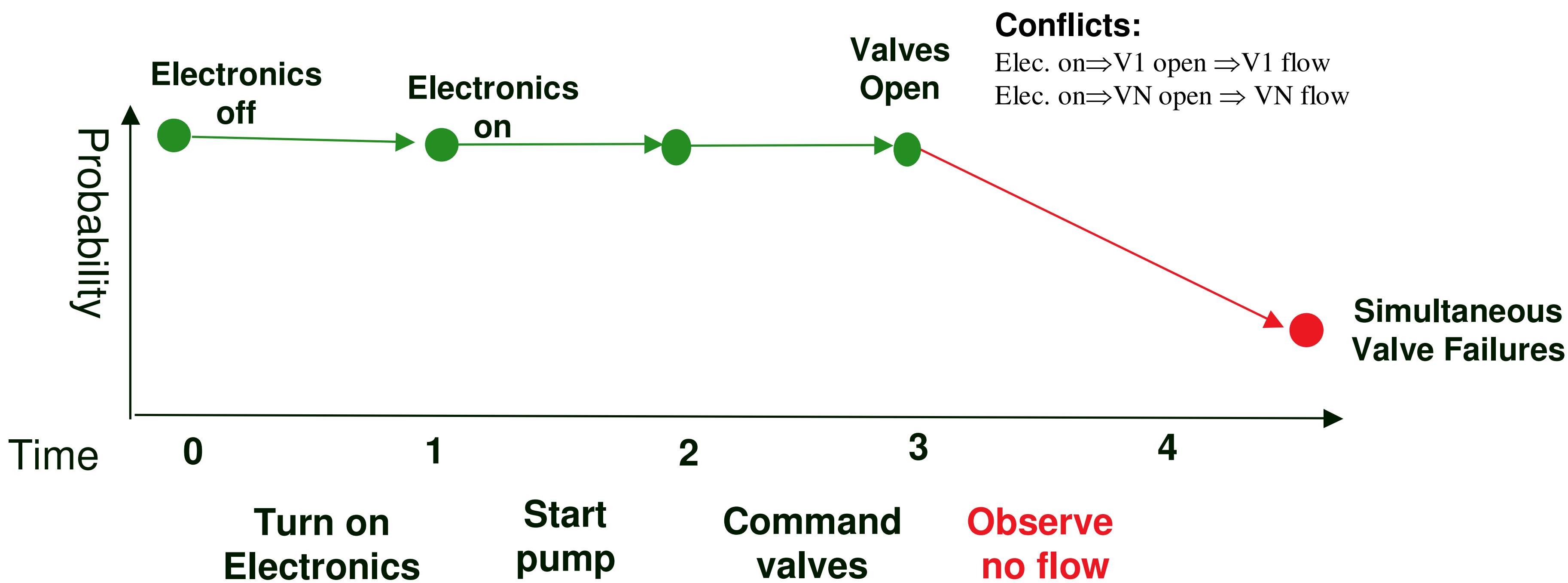
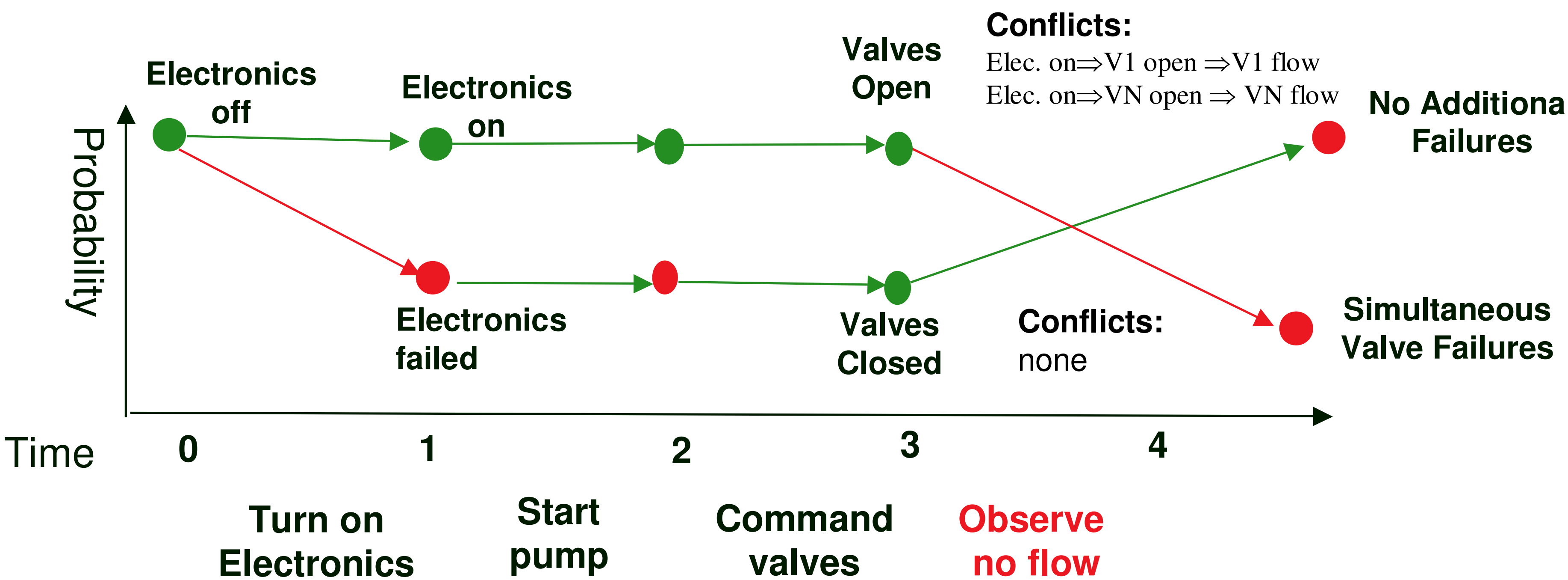
Generating Trajectories Incrementally



Generating Trajectories Incrementally



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Approach

- Create a structure that can enumerate every possible trajectory of the system
- Enumerate N trajectories that are consistent with observations thus far
- Extend each trajectory as actions are taken
- When trajectories are knocked out by new observations, incrementally generate the next most likely trajectory

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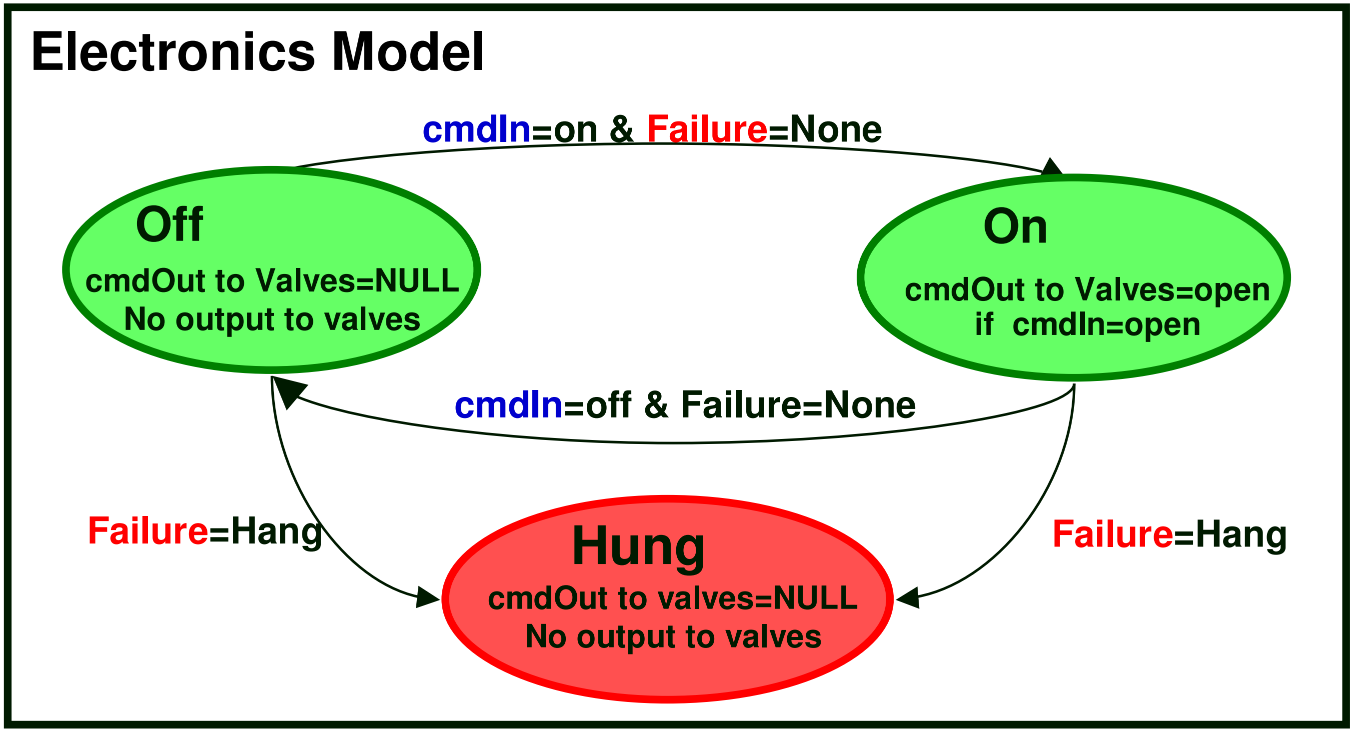
Encoding Device Behavior



Prior Probabilities

Value	P(**Failure**=Value)
None	α
Hang	$1-\alpha$

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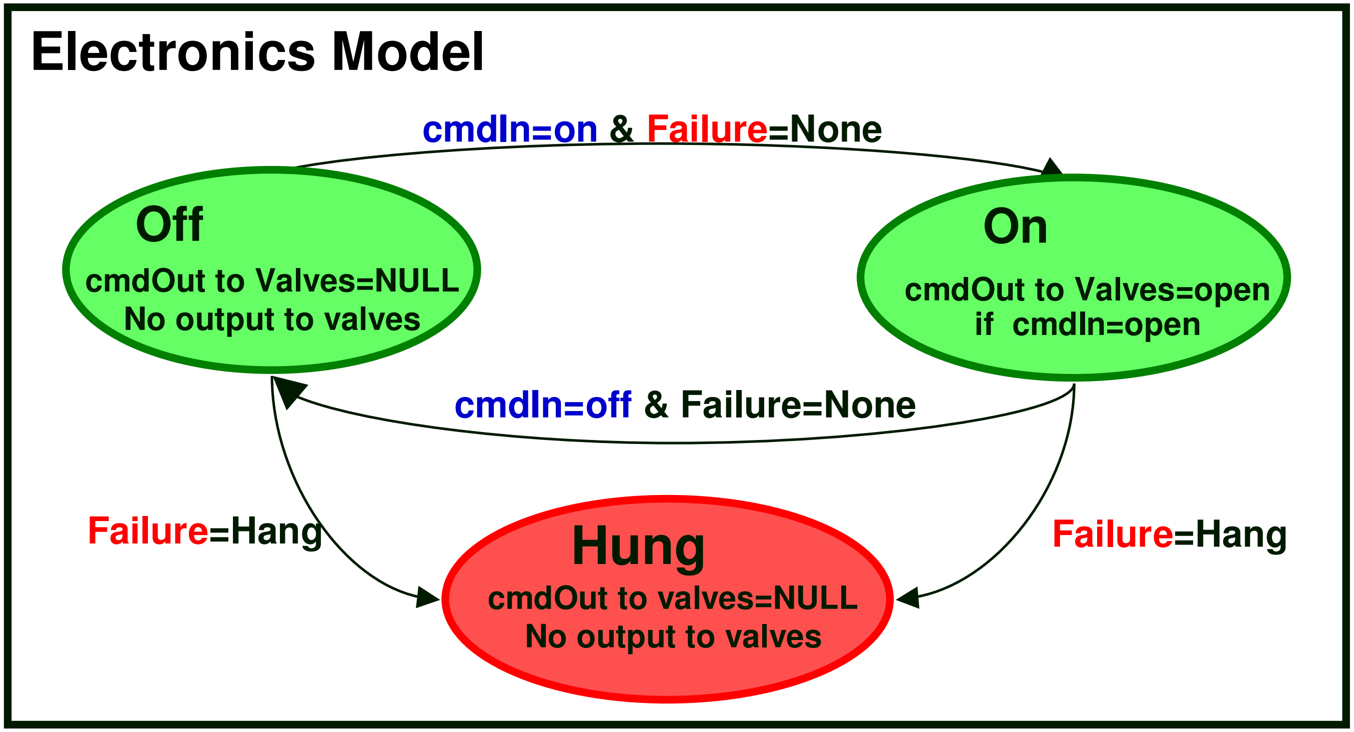
Encoding Device Behavior



Constraint Representation

Mode Behavior

mode=Off ⇒ cmdOut=NULL

Transitions	Time t	Time t+1
mode=Off & cmdIn=off & Failure=None ⇒		mode=Off
	Failure=Hang ⇒	mode=Hung

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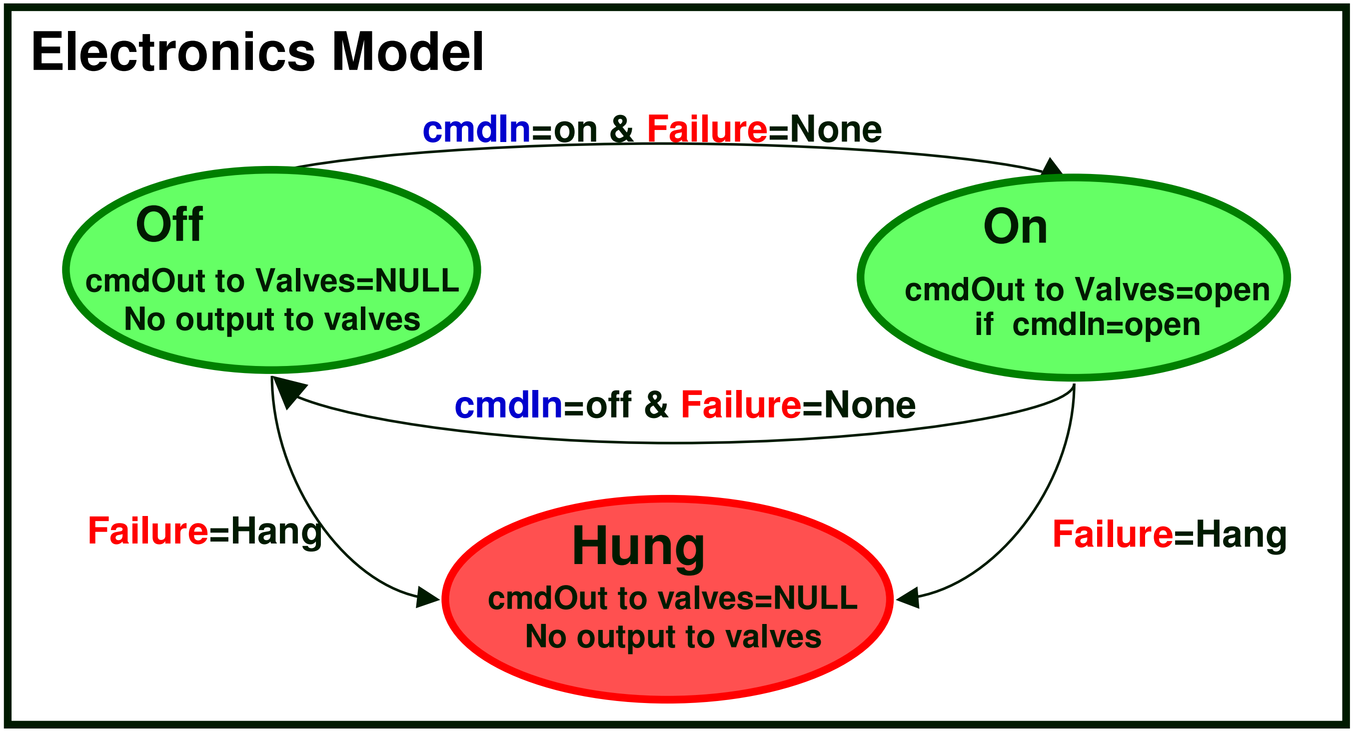
Encoding Device Behavior



Constraint Representation

Mode Behavior

mode=Off $\Rightarrow$ cmdOut=NULL

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	mode=Off & cmdIn=off & Failure=None $\Rightarrow$	mode=Off
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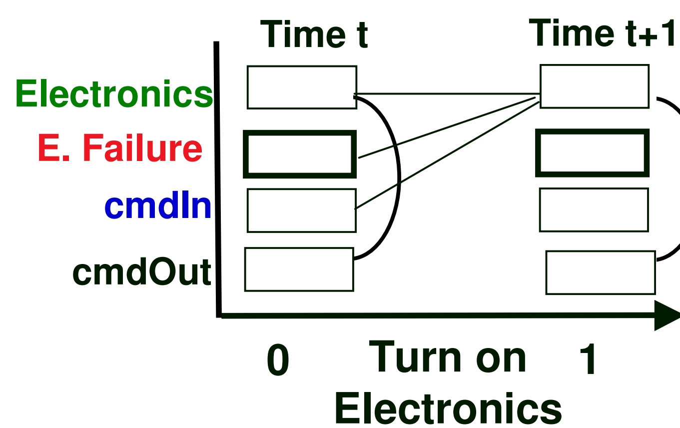
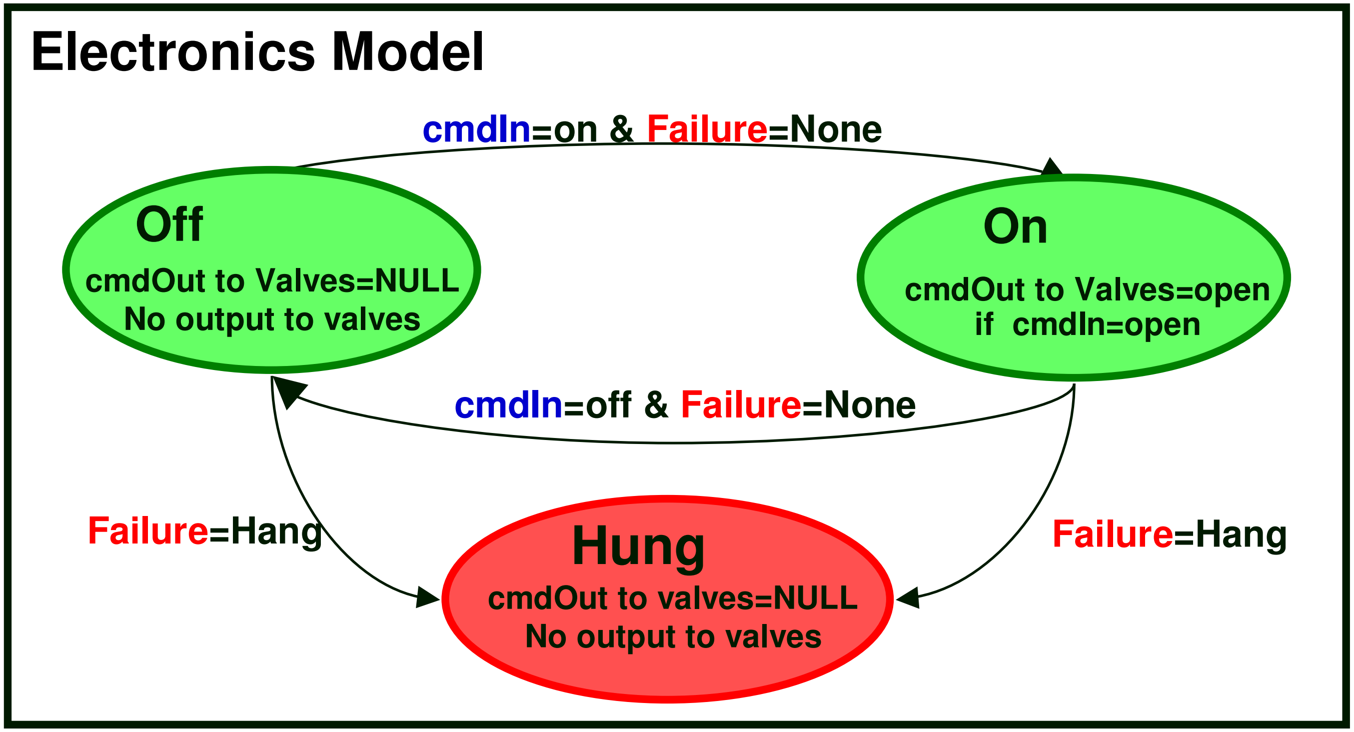
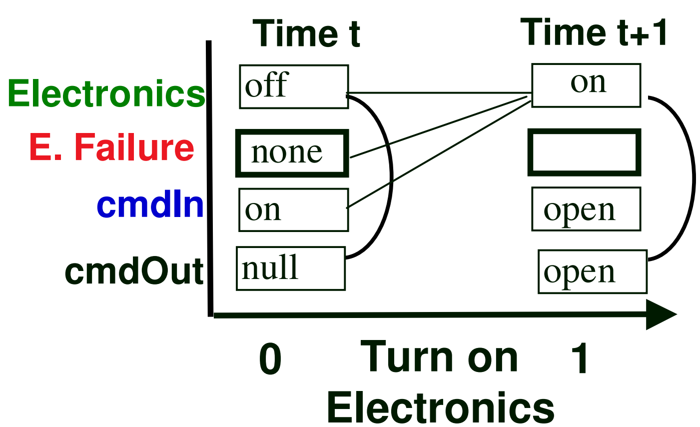
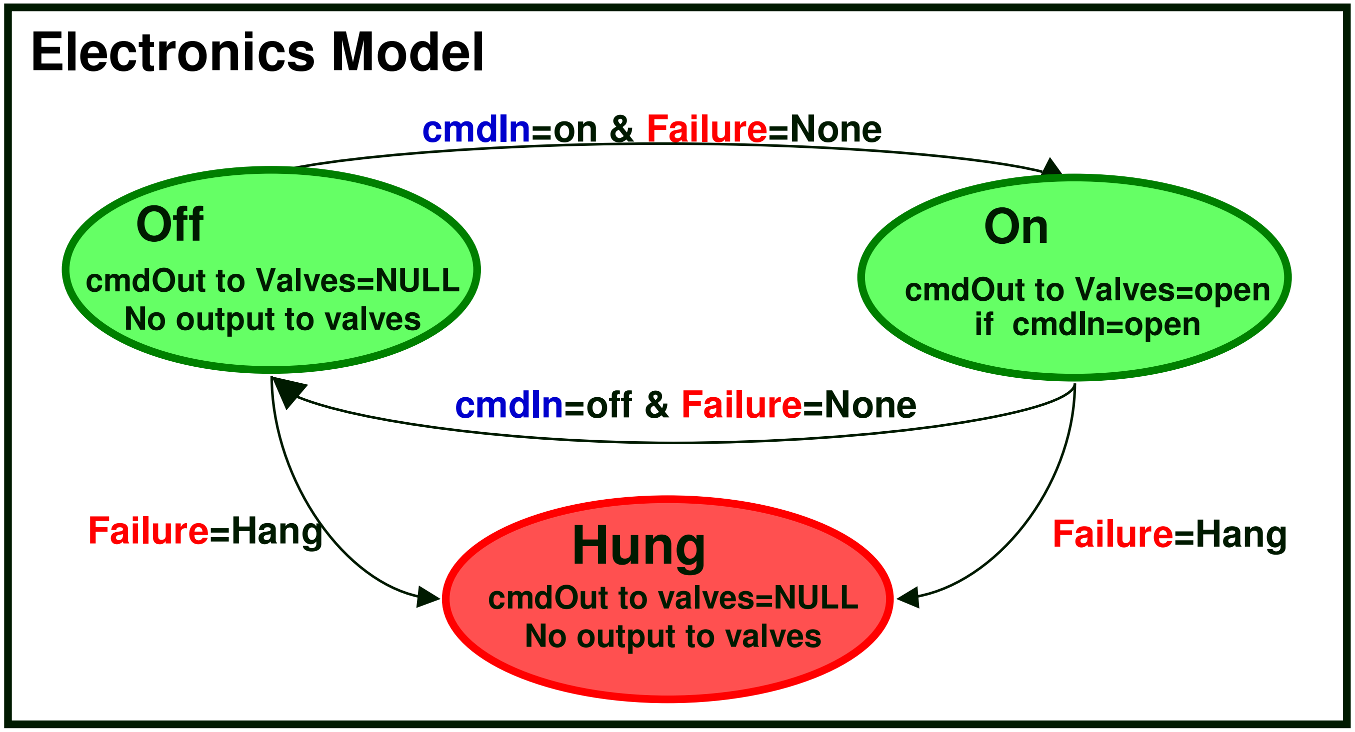


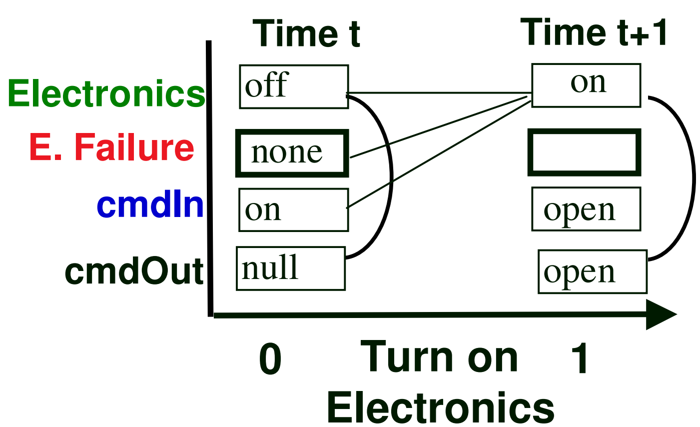
Encoding Device Behavior

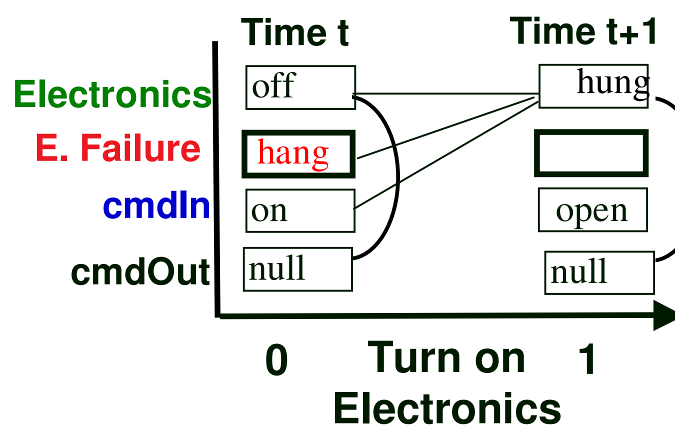




Encoding Device Behavior







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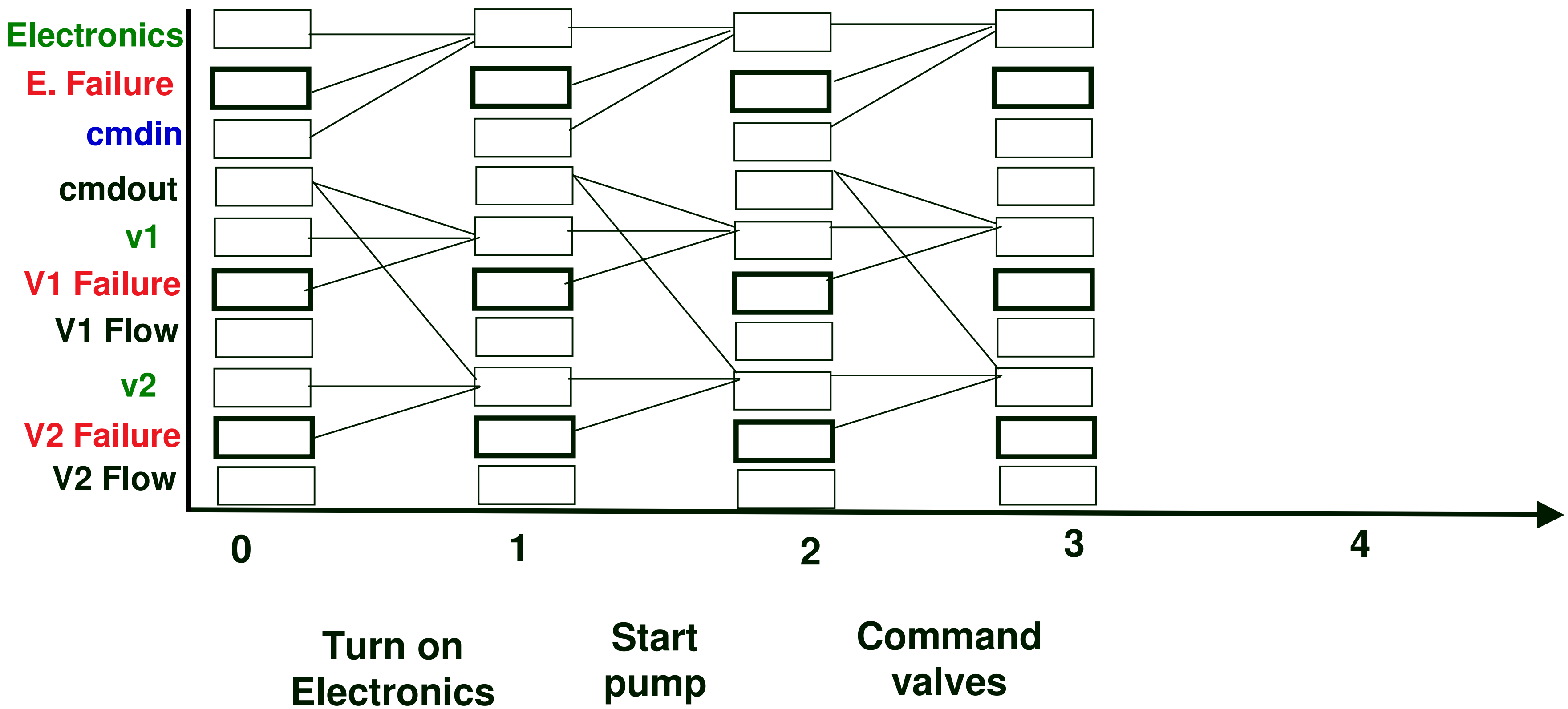
Trajectory Representation



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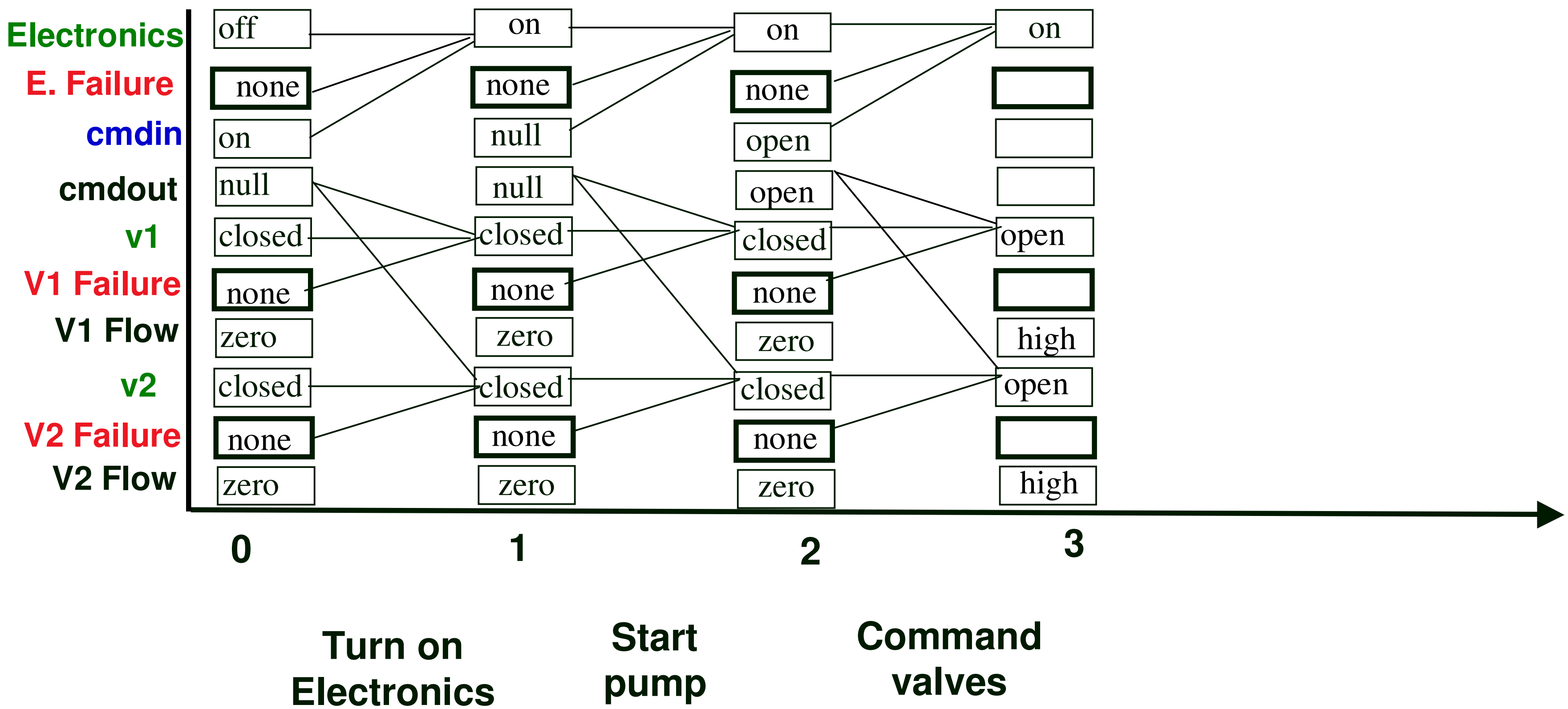
Trajectory Representation



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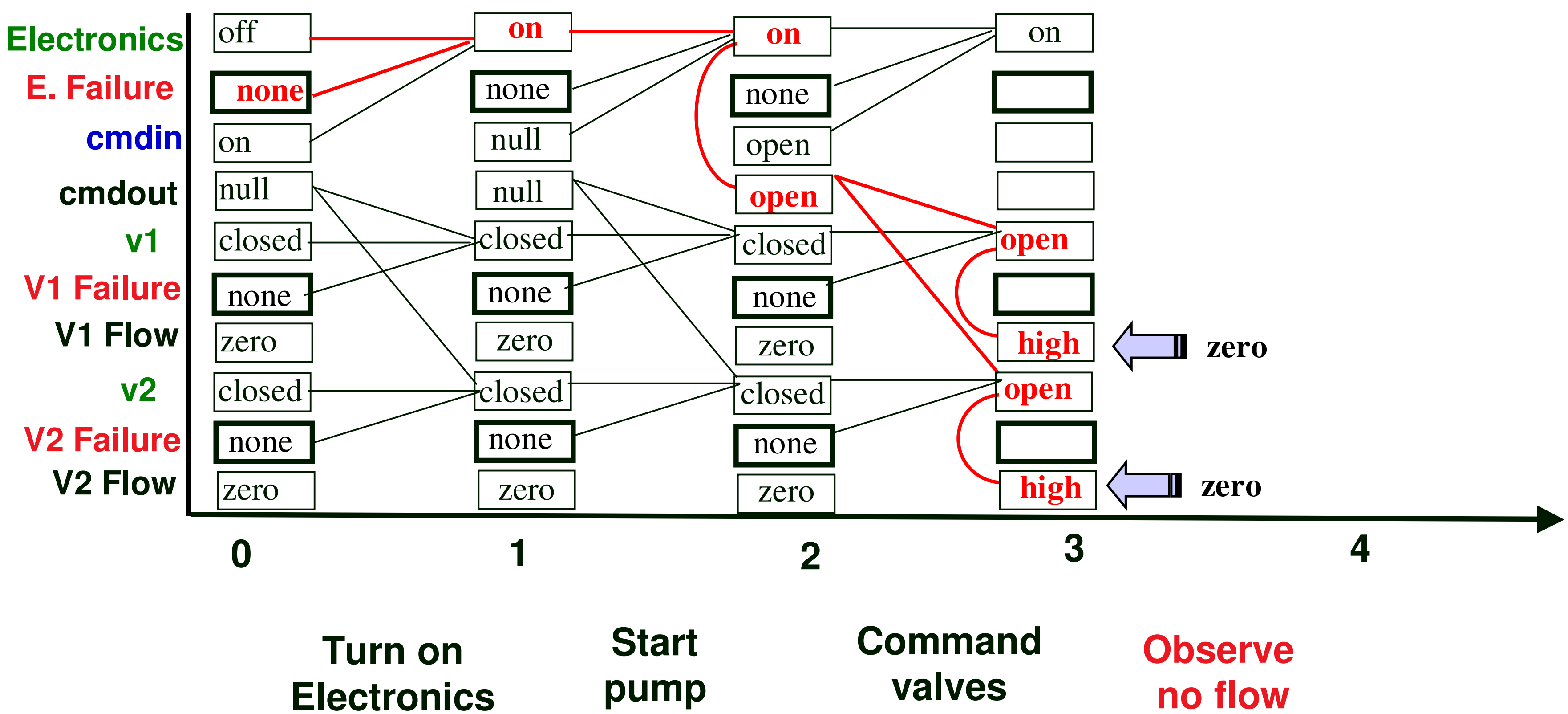
Trajectory Representation



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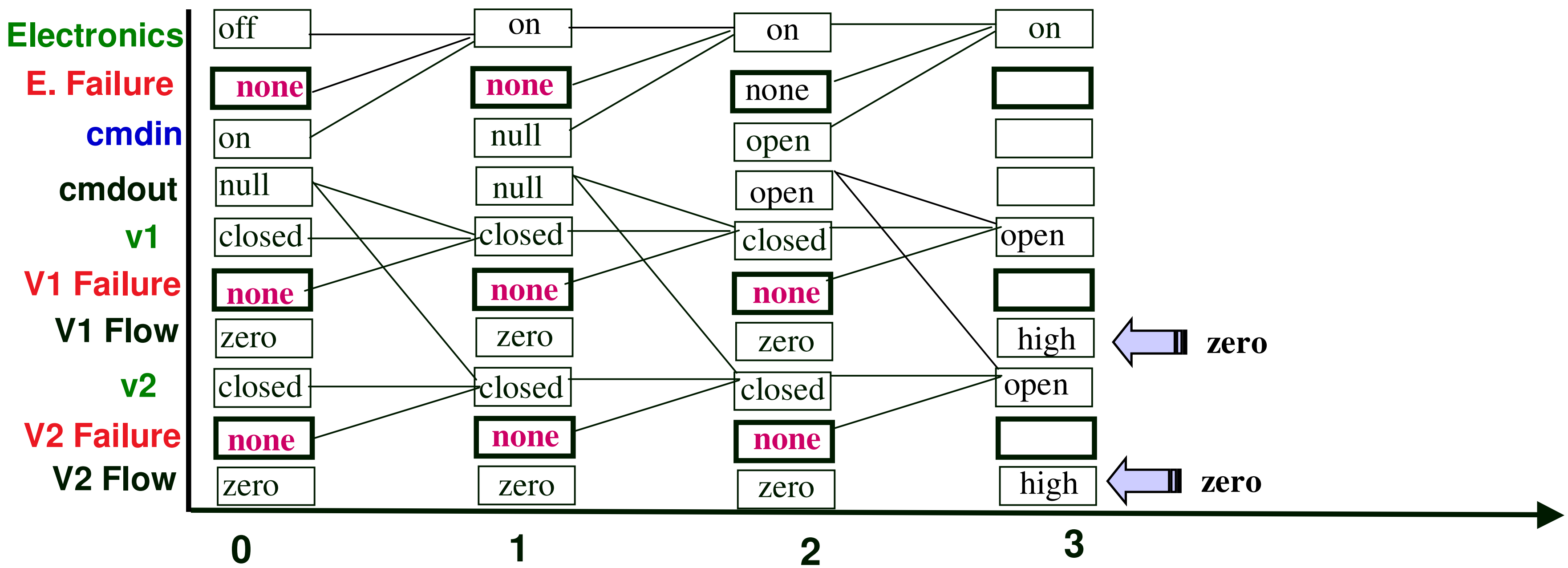
Generating No Goods

No Good: An assignment that conflicts with observations



- Every superset of a No Good is implicitly ruled out
- The most likely diagnosis differs from every No Good
- We can use conflict-based search (de Kleer & Williams 1989)

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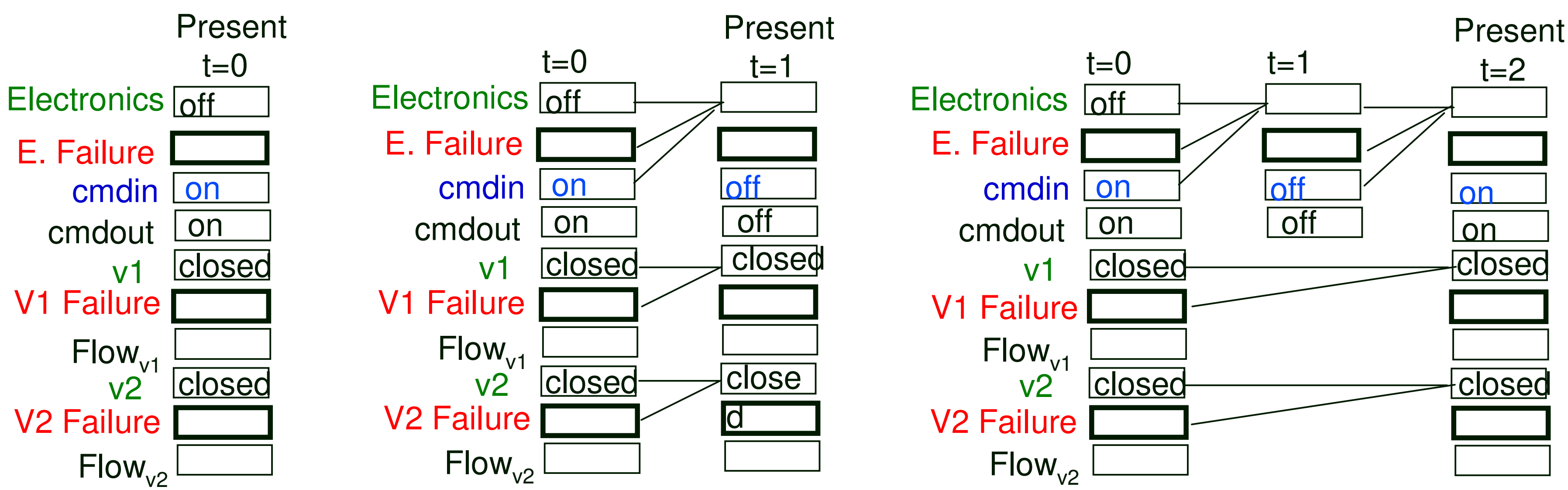
Minimizing Each Time Step

- Intuition: Many temporal distinctions are irrelevant
- Leverage: Merge times *t* and *t-1* for for irrelevant variables



- Proven to be a conservative approximation

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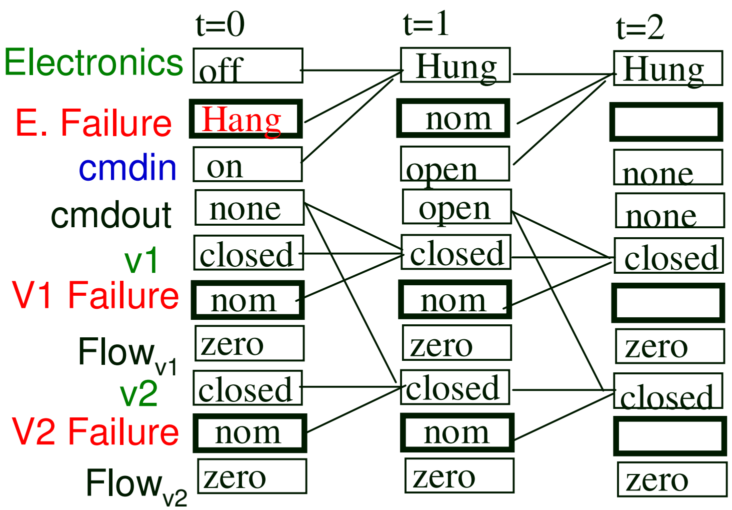
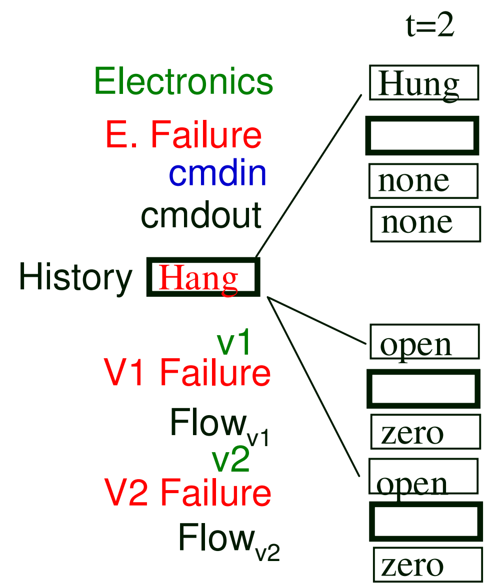
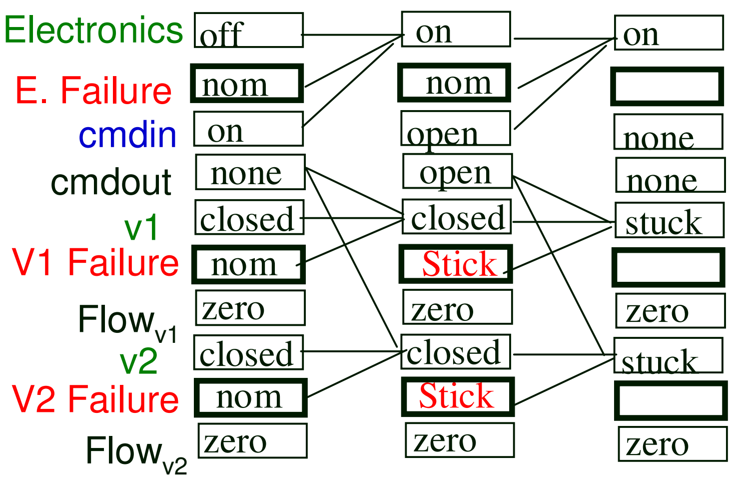
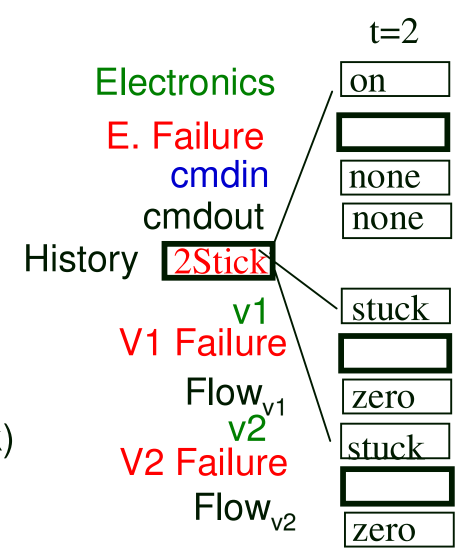
Truncating the Representation





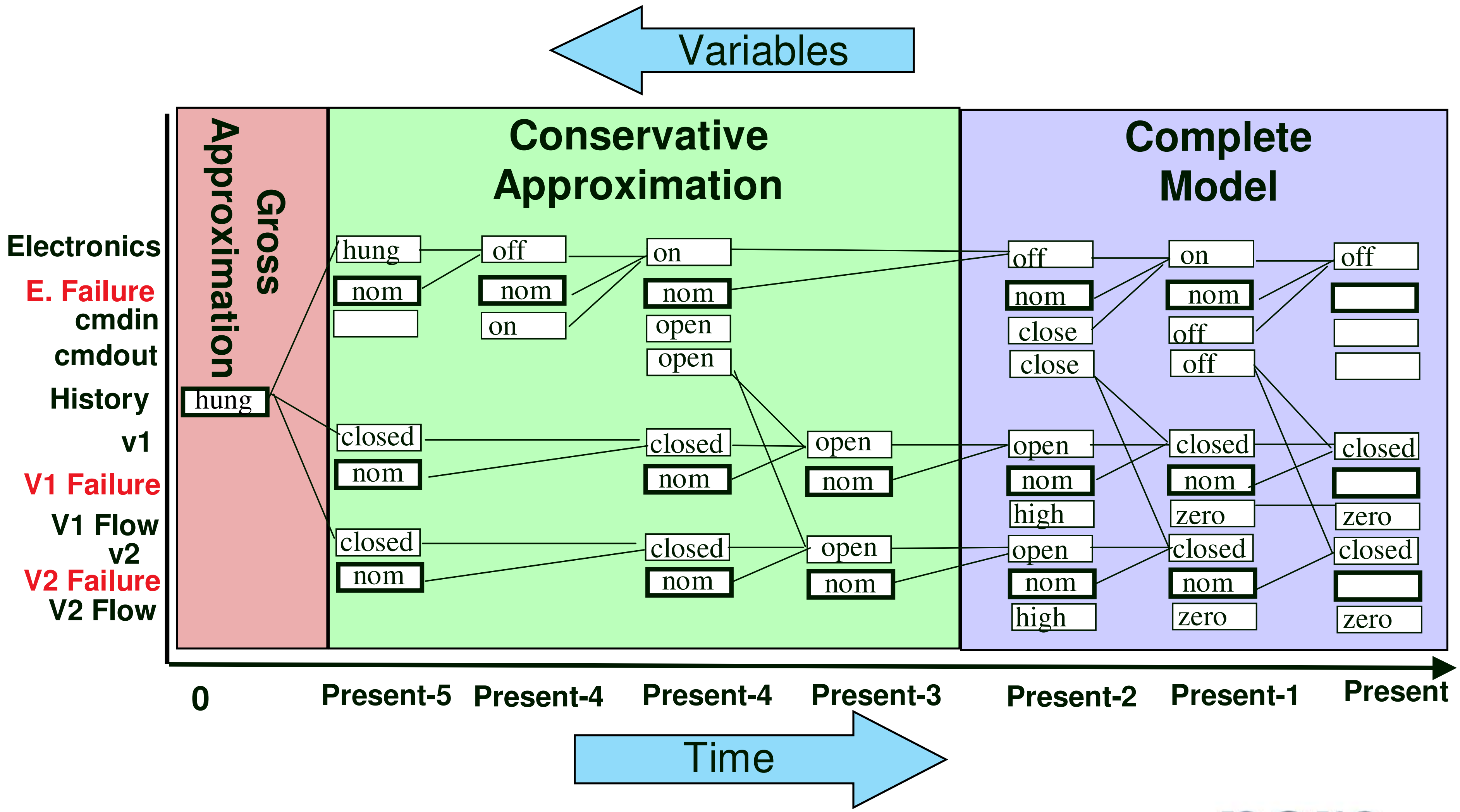
P(History=hang)=
P(hang)





P(History=2stick)=
P(stuck)*P(stuck)

Complete Representation



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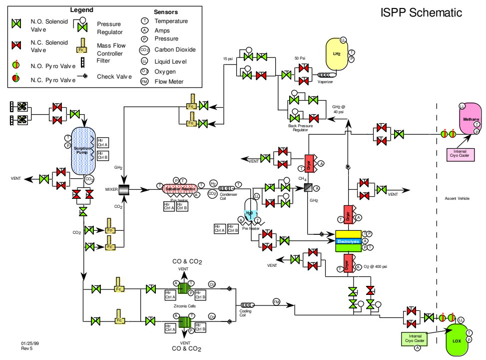
L2 Contributions in Diagnosis



- Developed novel representation for diagnosis over time
- Demonstrated low growth and also constant sized approximations
- Developed novel algorithm for finding all same-probability diagnoses
- Results published in Kurien and Nayak, AAAI 2000
- Significant real-world validation performed
  - Engineers modeled the X34 and X37 and ran diagnostic scenarios
  - Available for non-profit use and for-profit licensing from NASA

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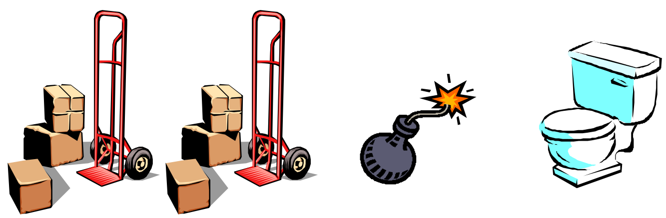
Performance on Bomb in the Toilet Problems

Packages	Toilets	FragPlan	HSCP	GTP	CMBP
6	1	0.11	0.01	0.07	0.01
8	1	0.47	0.01	0.11	0.20
10	1	2.89	0.01	1.31	0.71



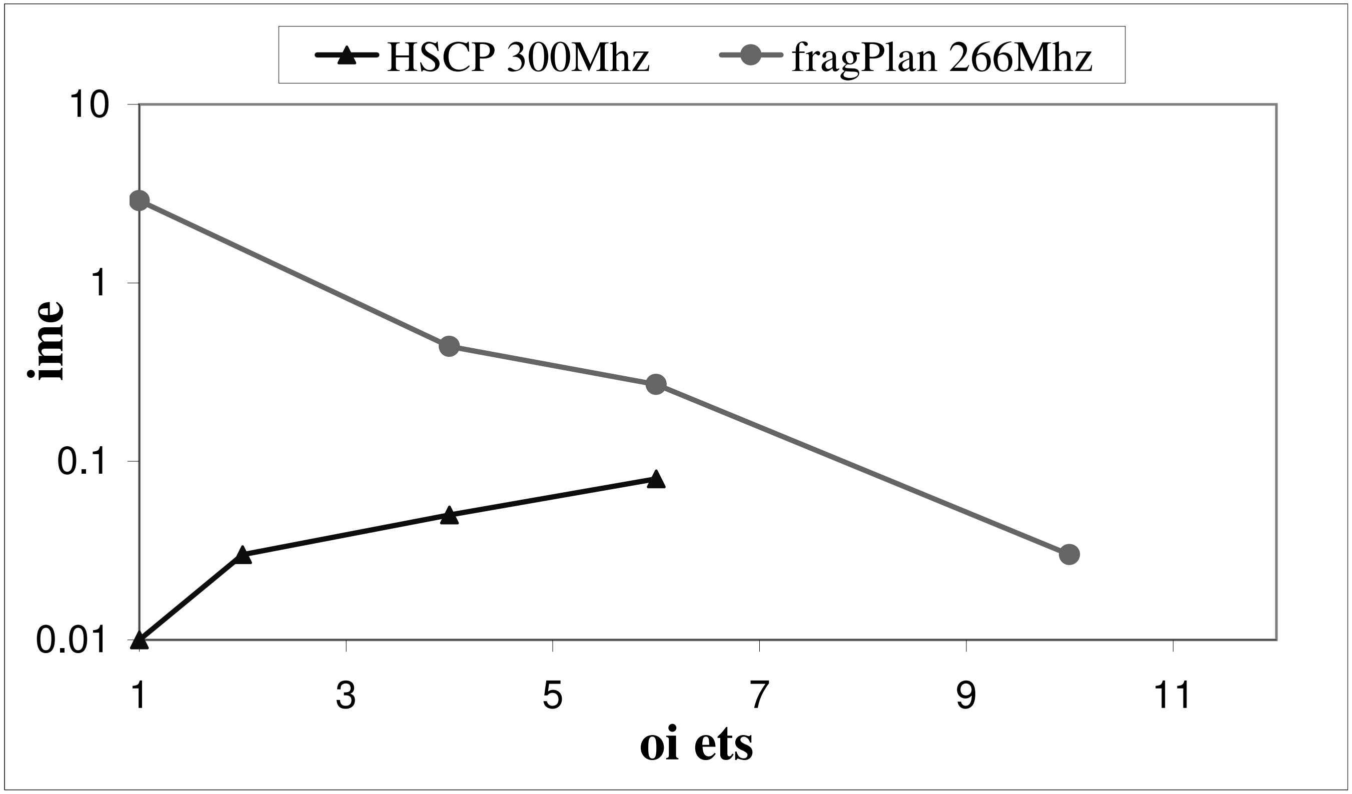
- HSCP dominates on serial (single toilet) instances
- FragPlan is competitive with GTP, CMBP

Bomb in the Toilet with Parallelism

Packages	Toilets	FragPlan	HSCP	GTP	CMBP
8	1	0.47	0.01	0.11	0.20
8	4	0.23	0.04	8.78	2.74
8	6	0.05	0.08	68.43	20.71

- HSCP, CMBP, GPT cannot produce parallel plans
- They produce much longer, harder, serial plans
- Only FragPlan & C-Plan (not shown) are truly parallel
- C-Plan fails on most serial instances

Bomb in the Toilet with Parallelism



- Space of serialized plans explodes as parallelism increases
- Fragments become independent, yielding linear speedup

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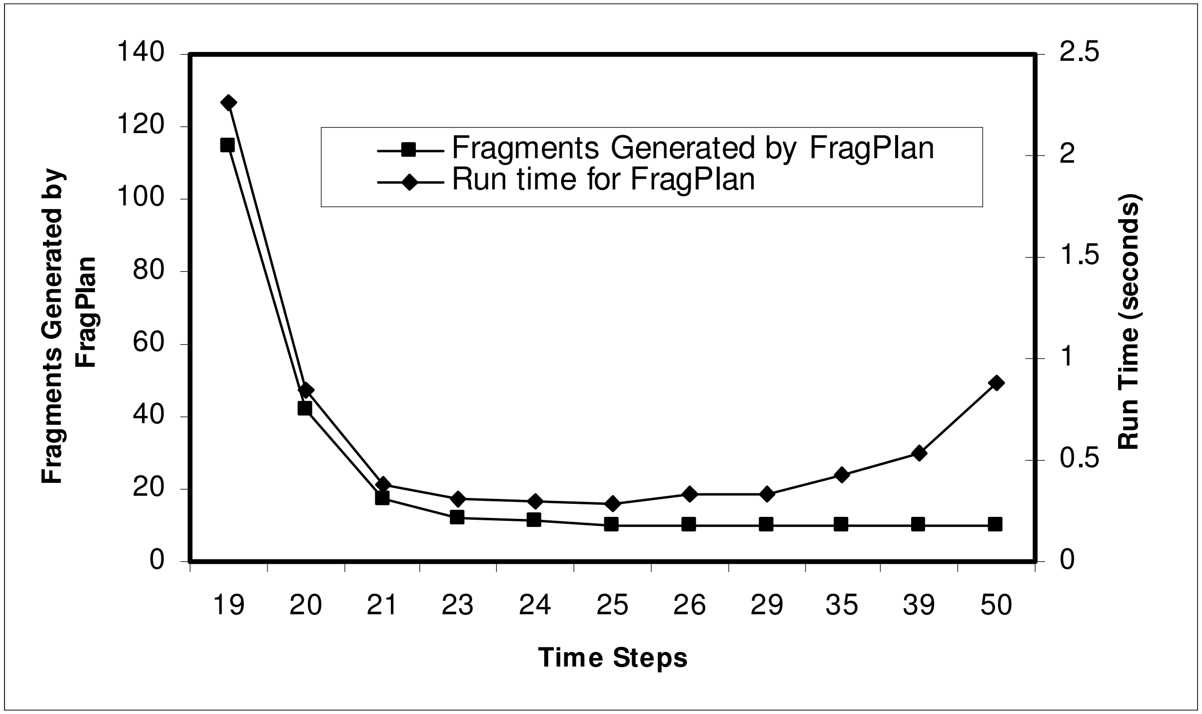
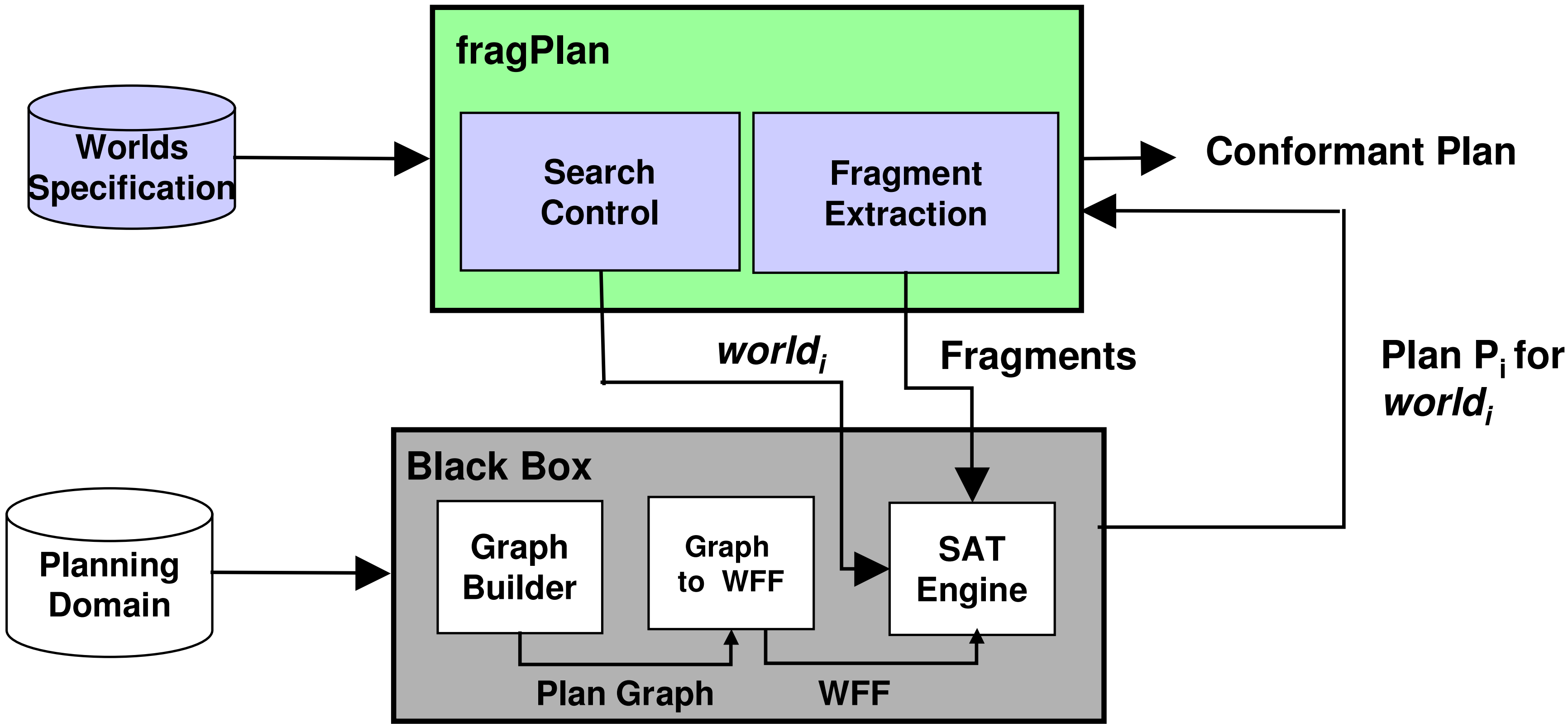
Planning with Extra Time Steps



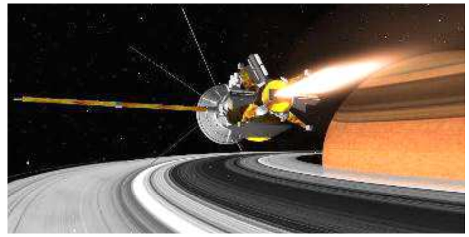
- For fragPlan, density of conformant plans rises
- For other planners, search depth grows

Implementation



- We currently use Black Box (Kautz & Selman 99) as a black box
- Black Box encodes the problem as propositional satisfiability
- Randomized SATZ used to find an assignment (*i.e*. a plan)

Is Conformant Planning Enough?



- No conformant plan may exist due to failures
    - Some goals may not be achievable in any world
    - Some possible worlds may not allow all goals
- Certain actions may violate safety constraints
    - Safety always desired, often dominates
    - Certain goals dominate at critical junctures
    - A failure may force all actions to be unsafe
- Time for planning not known a priori
    - We must have some plan

Given: Partial ordering on goals, safety, and worlds
Return: Best plan the available time allows

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SCOPE – Safe, Conformant, Optimizing Planning Engine

- Approach: Manipulate the scope of the problem

While ($Time \neq 0$) {
  select constraints from $\{Worlds \cup G \cup S\}$
  FragPlan(constraints) for some time
  }

- Pareto-optimality requires checking all constraint subsets

- We have developed many simpler selection policies and experimented with several

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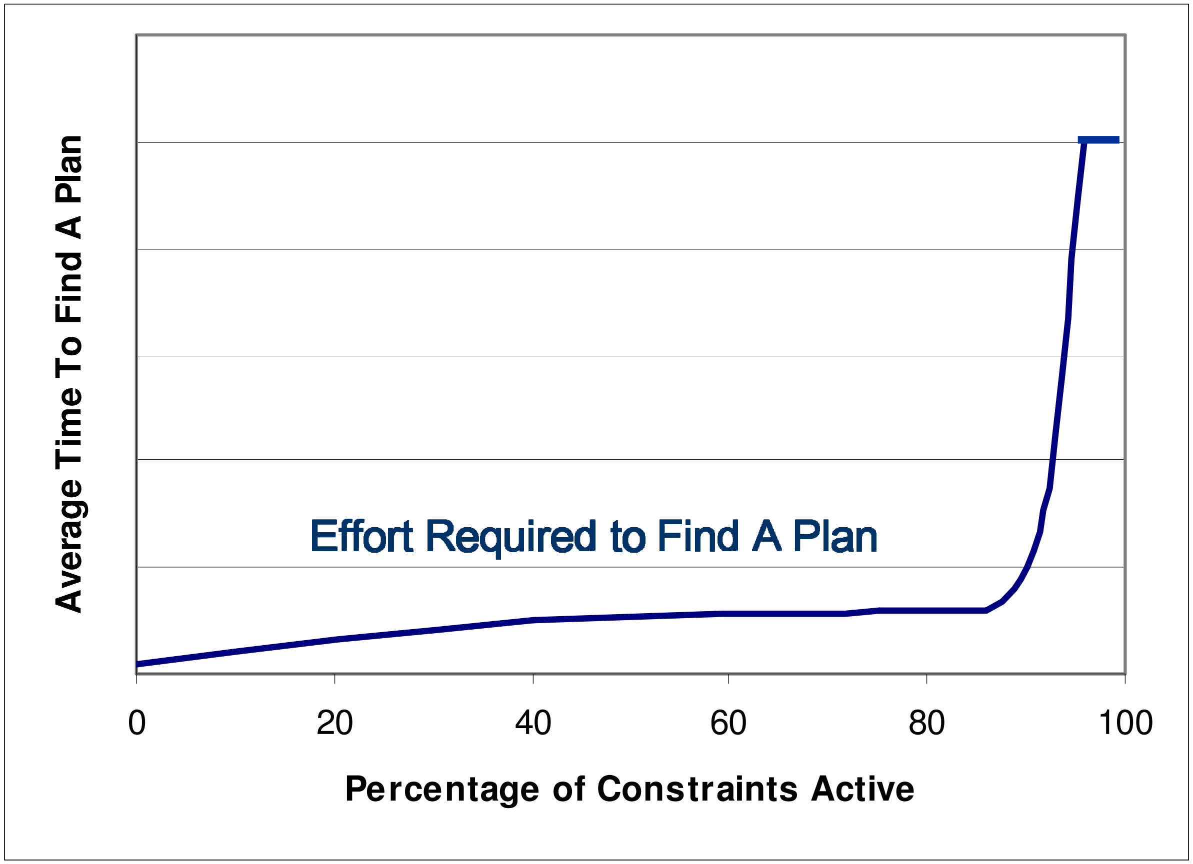
Typical Planning Problem Difficulty



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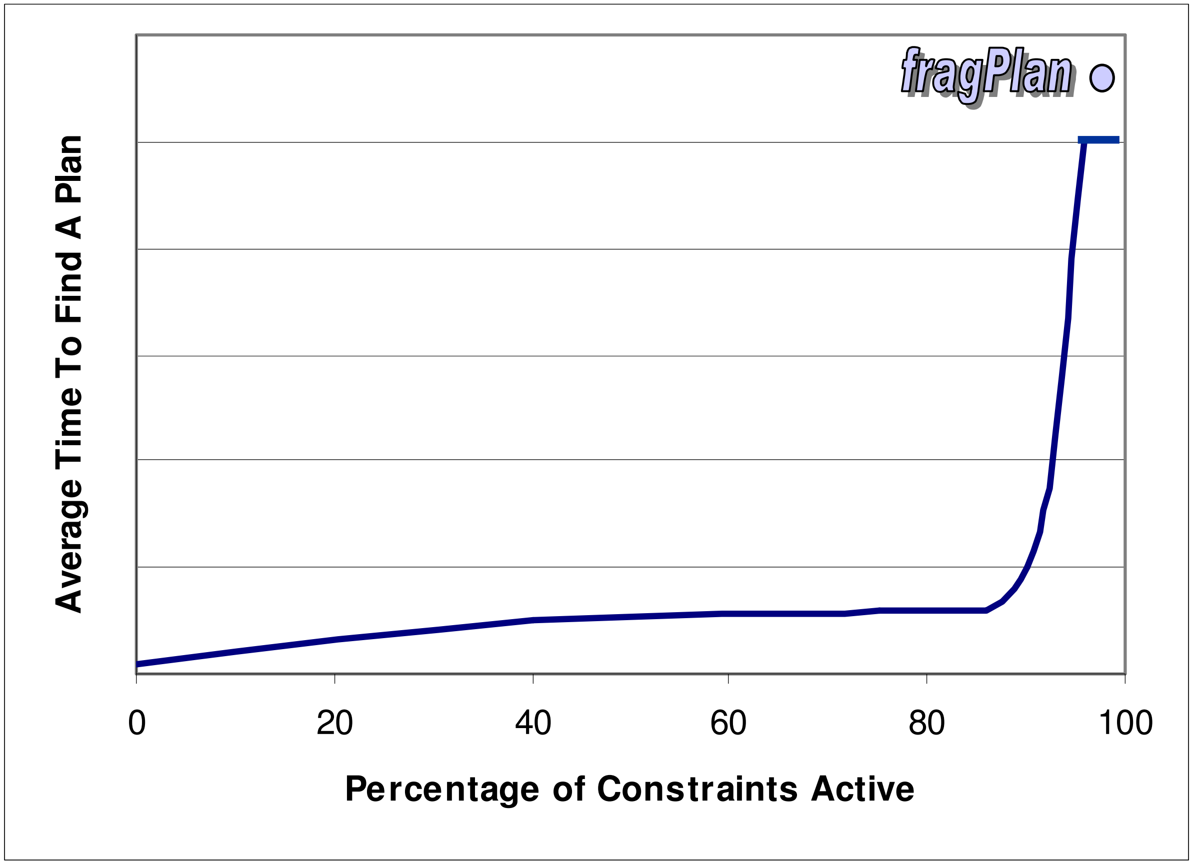
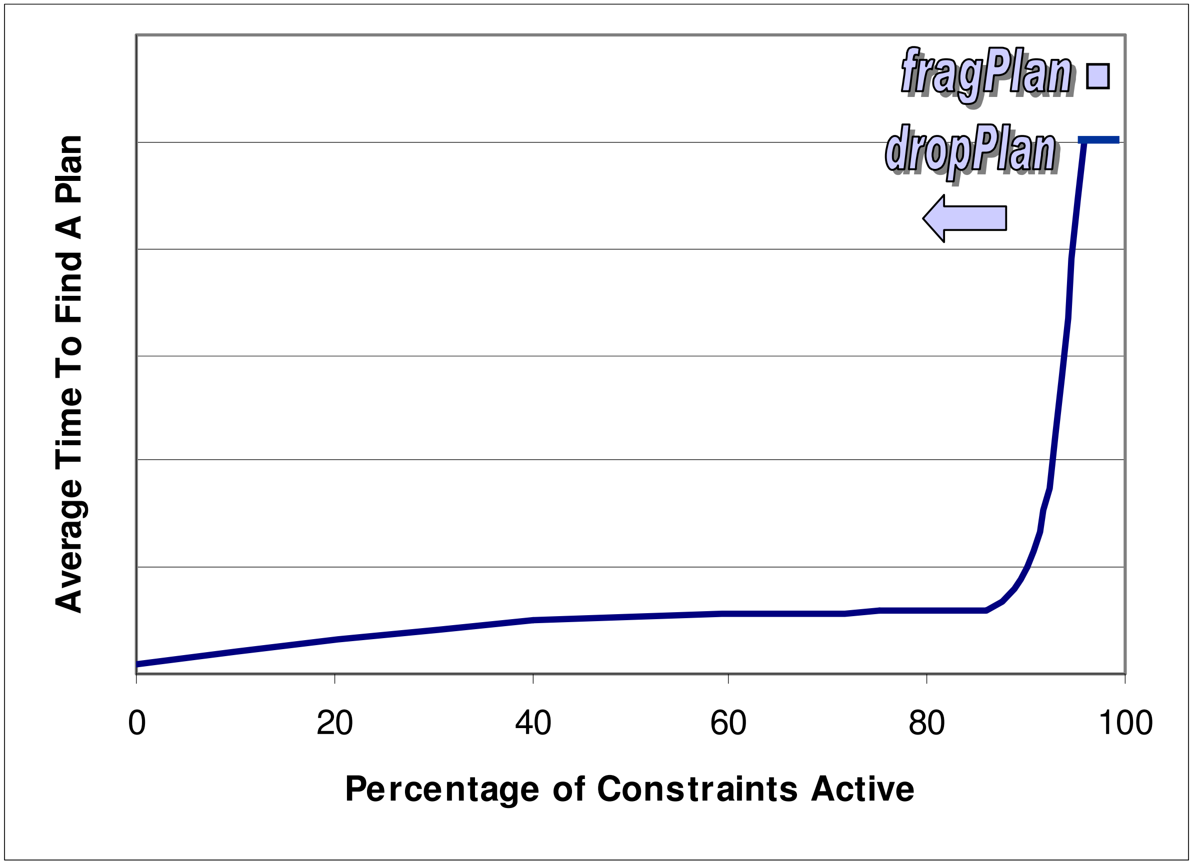
SCOPE Strategies



- fragPlan Strategy: Go for broke
  - Devote all time to solve entire constraint set

SCOPE Strategies



- dropPlan Strategy: Start big, shrink
  - Devote 1/n of remaining time to solve entire constraint set
  - Failure reveals difficult constraint combinations
  - On failure, remove constraints guided by O, difficulty

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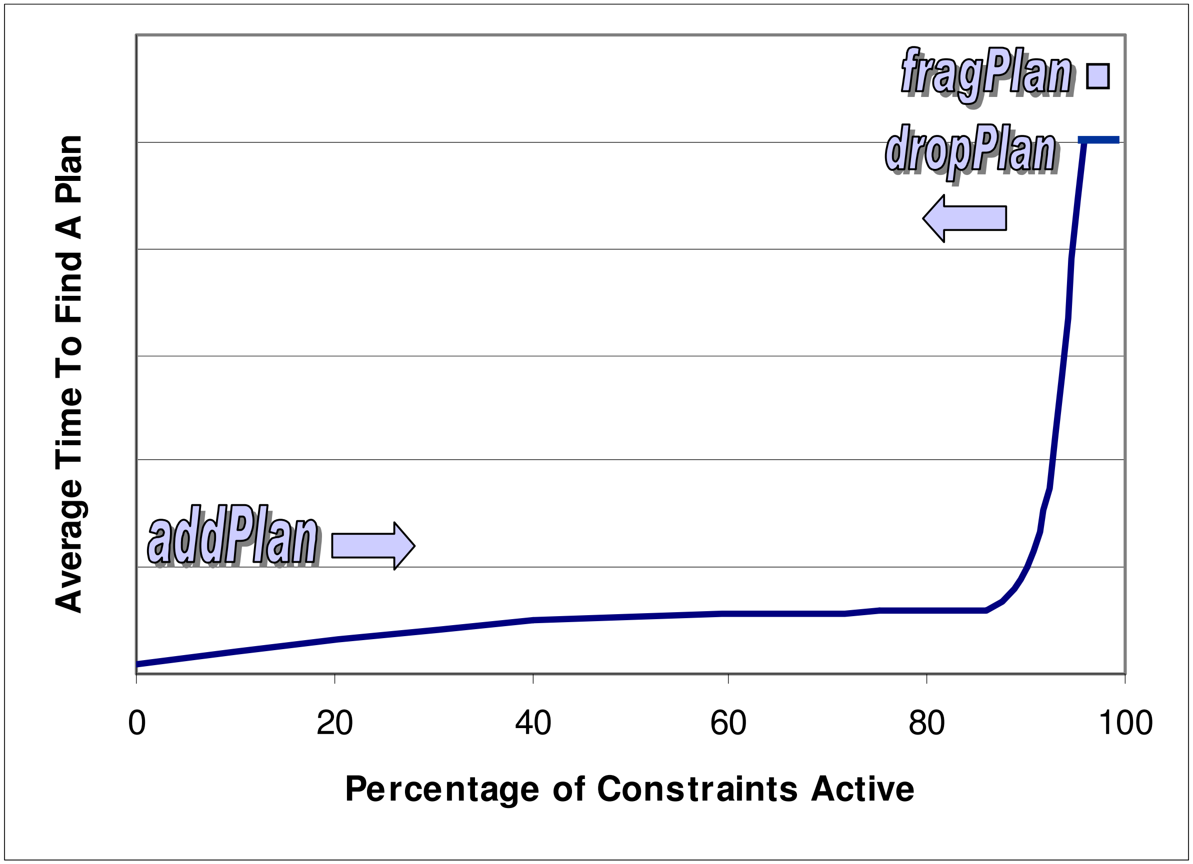
SCOPE Strategies



- addPlan Strategy: Start small and grow
  - Devote all remaining time to solving simplest problem
  - Anytime
  - On success, add constraints guided by partial ordering O
  - Successful plans used to seed next planning attempt

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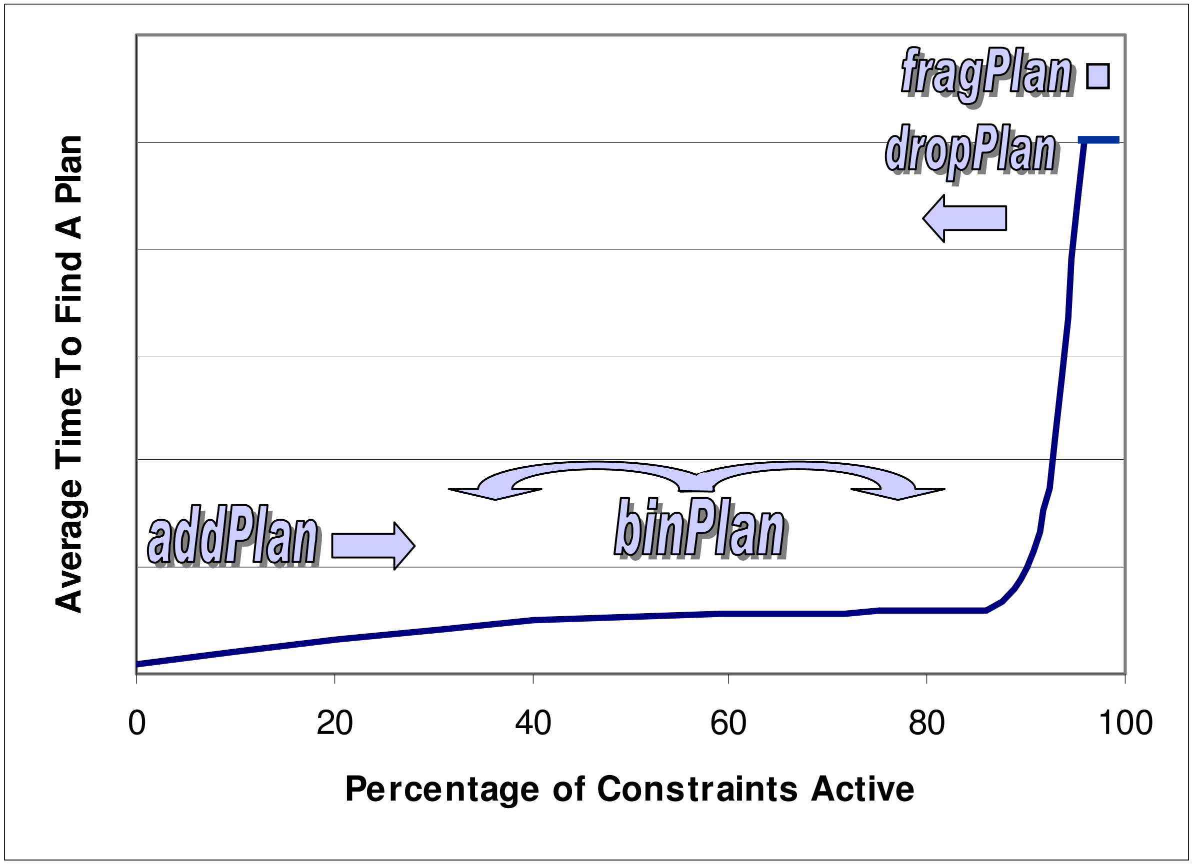
SCOPE Strategies



- binPlan Strategy: Start in the middle, grow or shrink
  - Attempts to rise faster than addPlan, fail less than dropPlan

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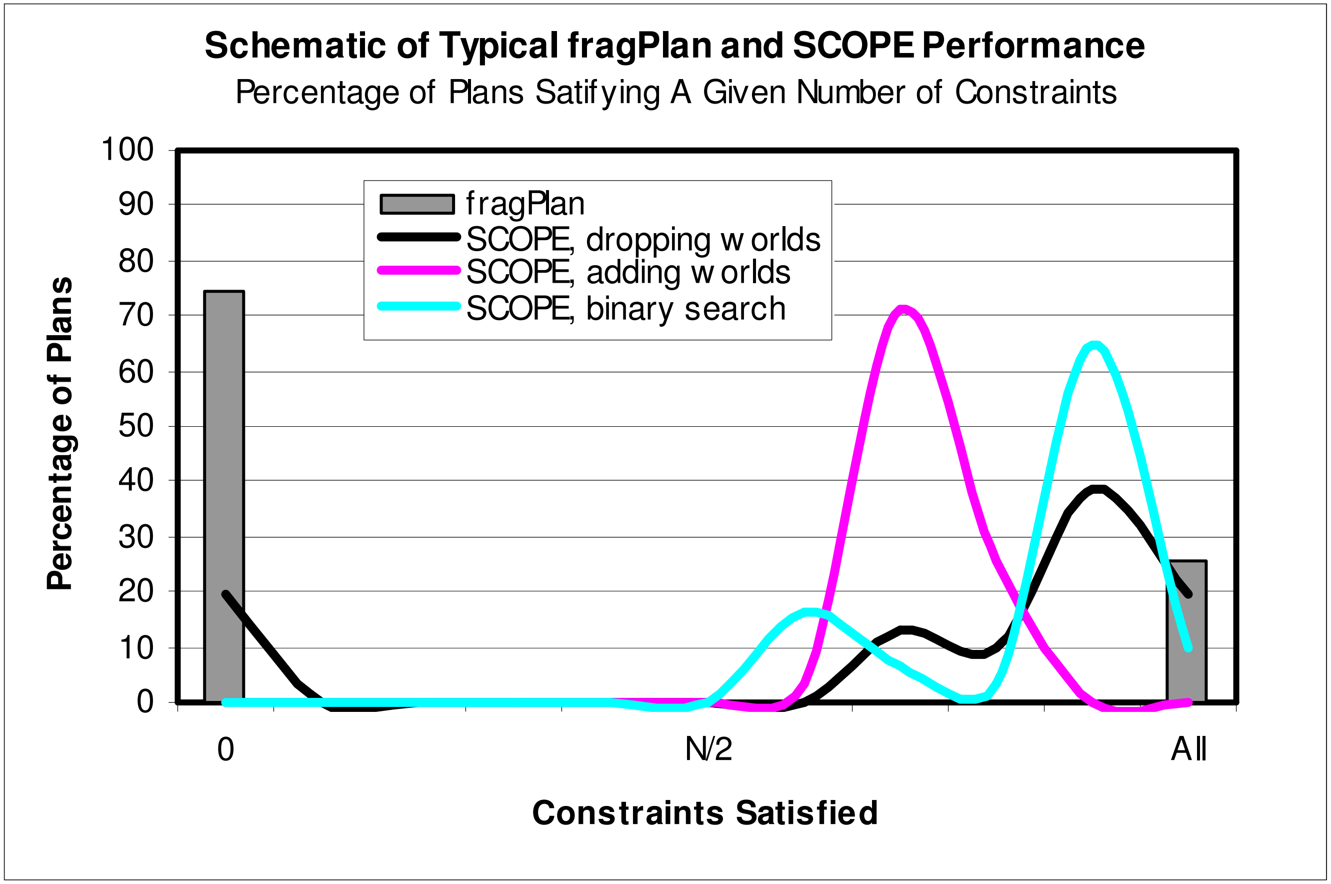
Some Observations On SCOPE

- fragPlan produces more conformant plans
- All SCOPE variations have better expected performance



Other Strategies

- We want the problem that is just short of too hard
- Intuitively, we attempt to learn the difficulty curve
- dropPlan with difficulty
  – When a plan fails, we can often identify the constraints at fault
  – We remove constraints that consistently cause problems
- addPlan with sliding
  – If the first plans are easy, move right faster
- Reversal of fortune
  – Start with all constraints and drop, learning difficulty
  – If time runs short, drop all constraints and add least difficult

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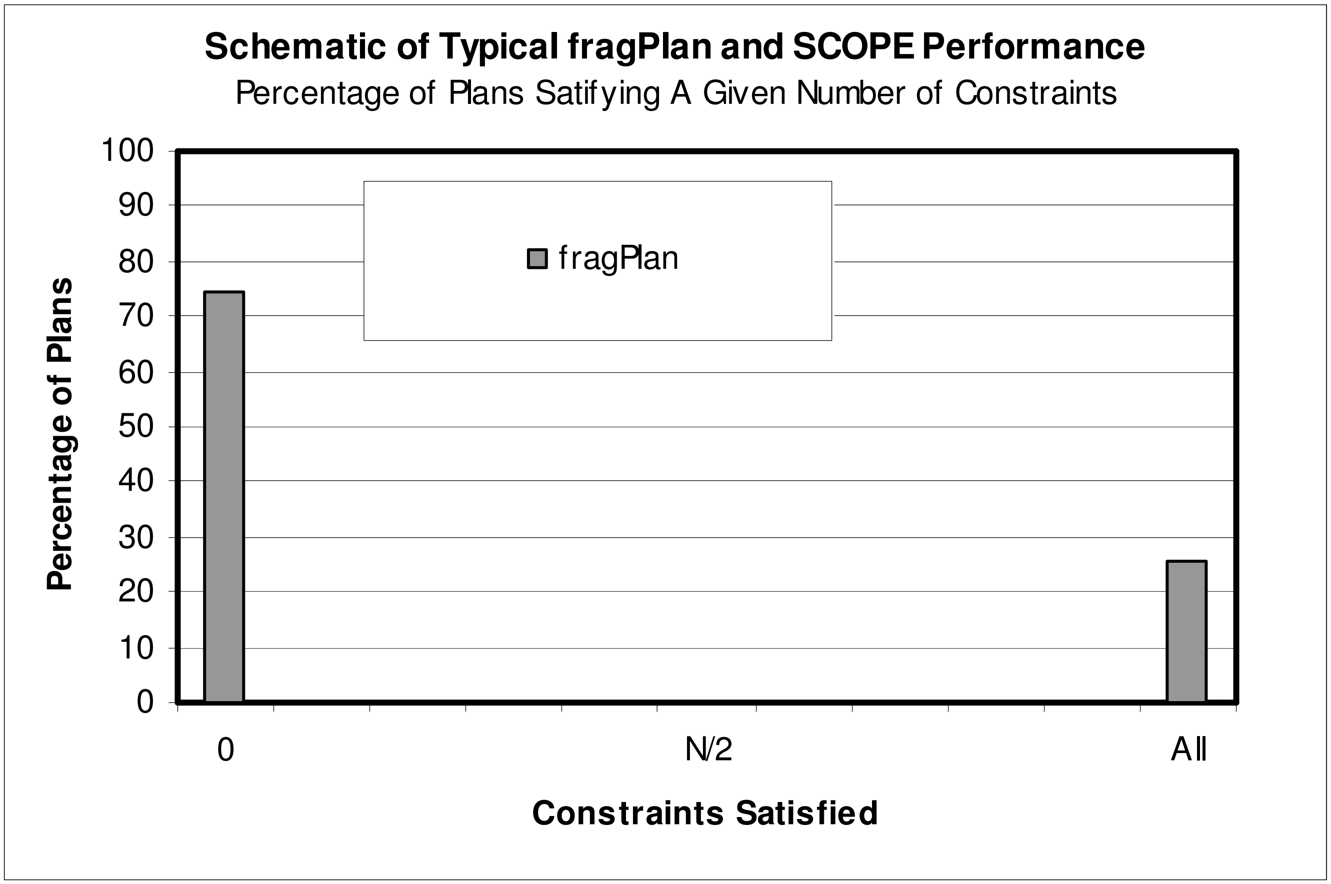
Typical Performance of fragPlan



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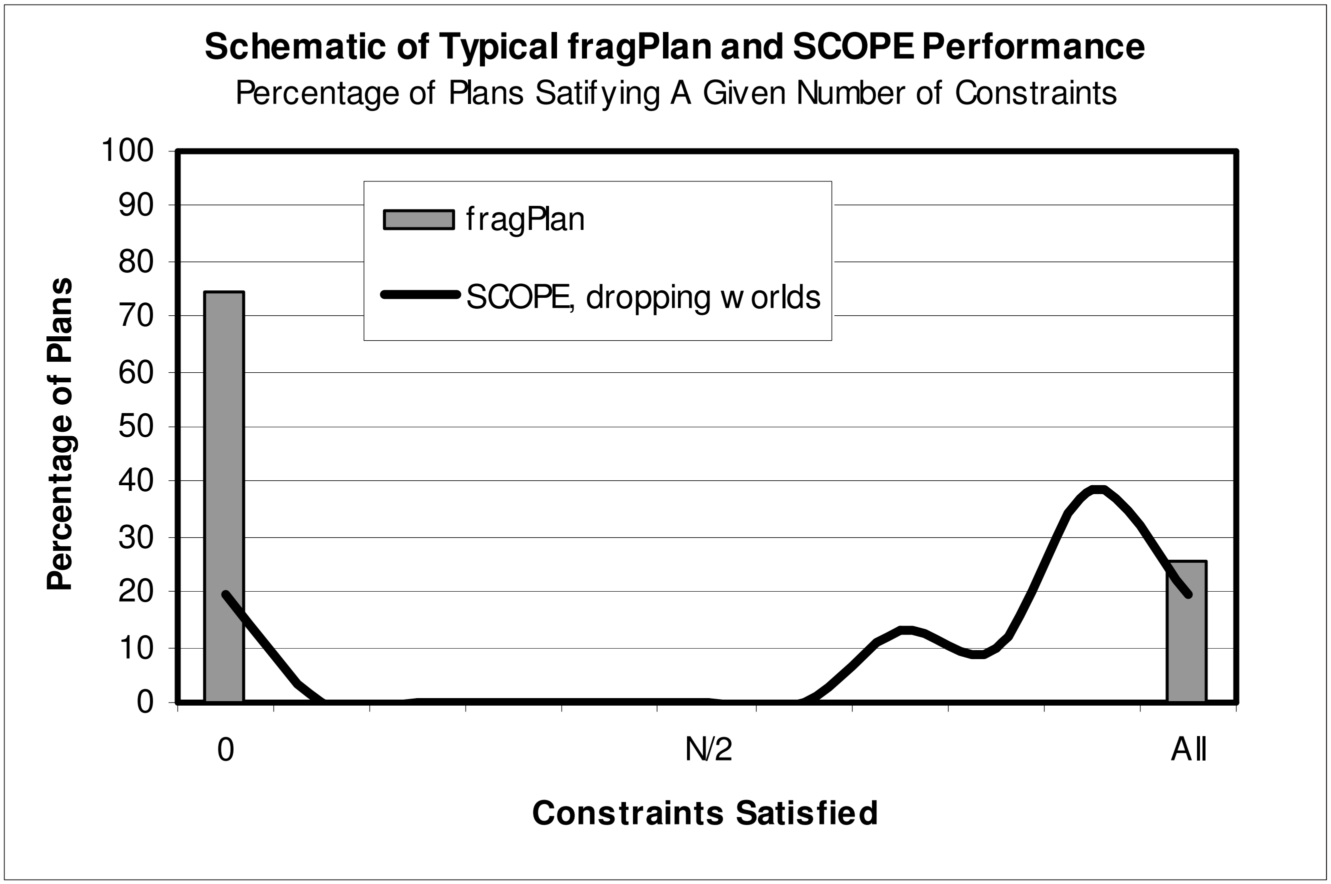
Typical Performance of fragPlan vs SCOPE



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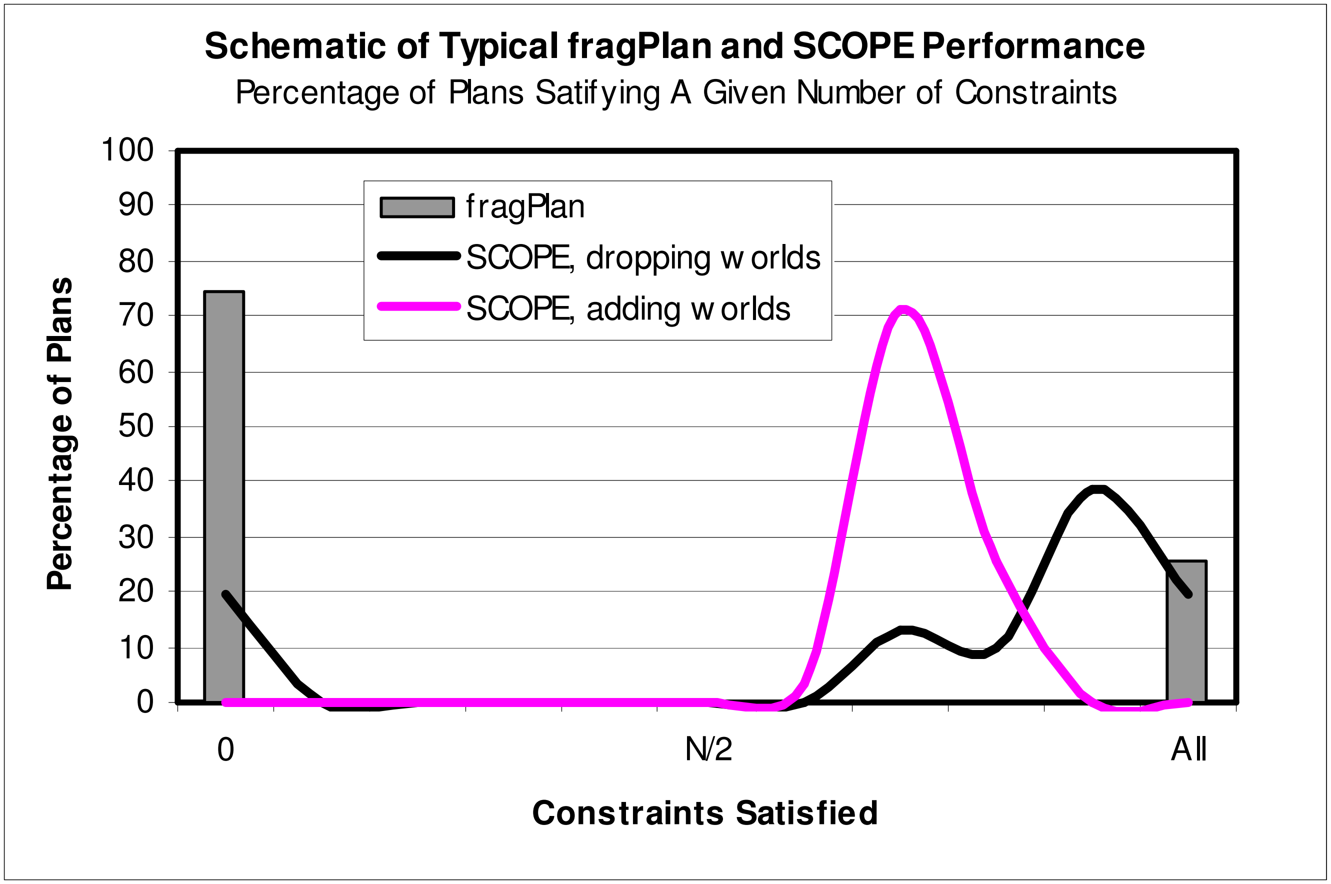
Typical Performance of fragPlan vs SCOPE



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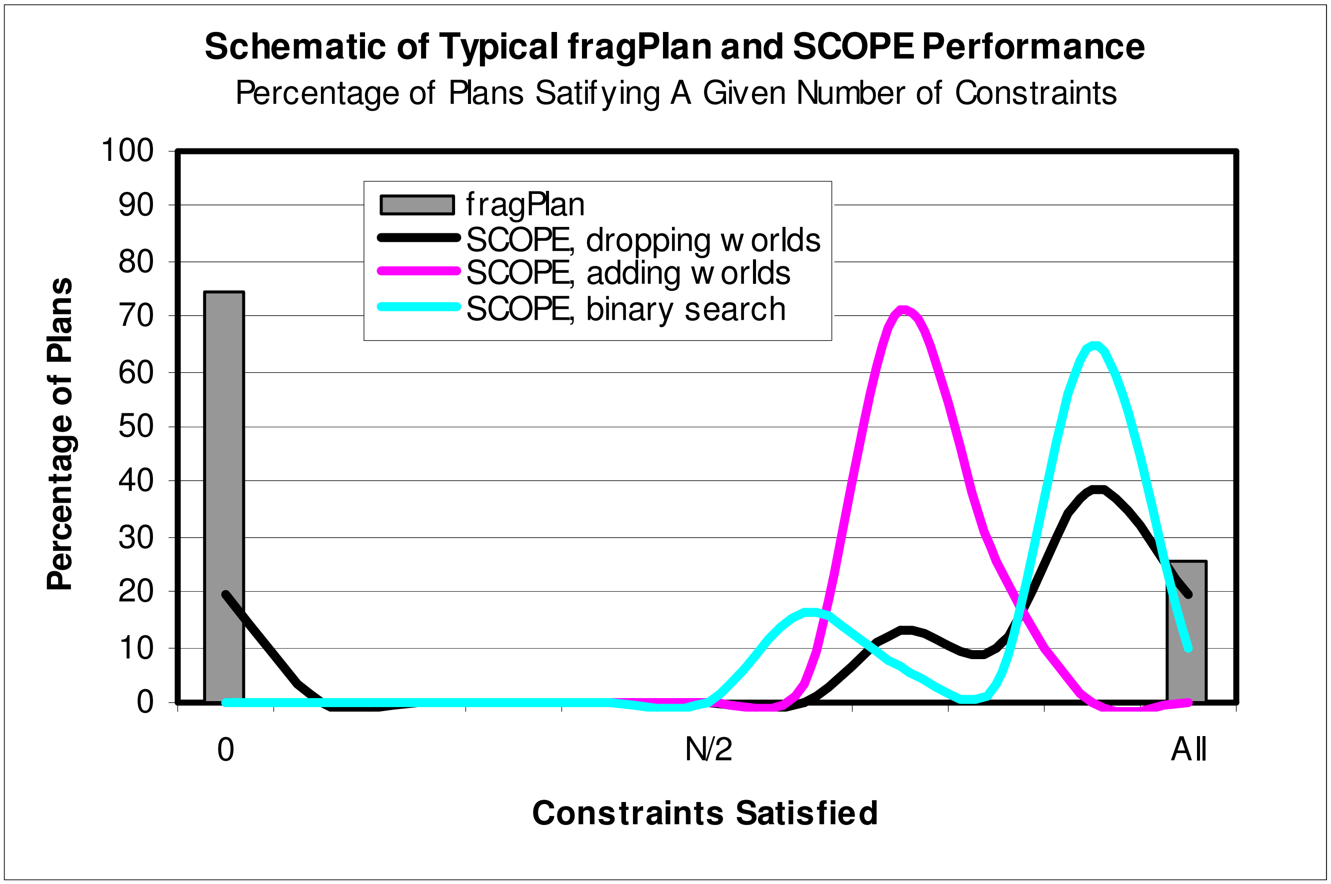
Typical Performance of fragPlan vs SCOPE



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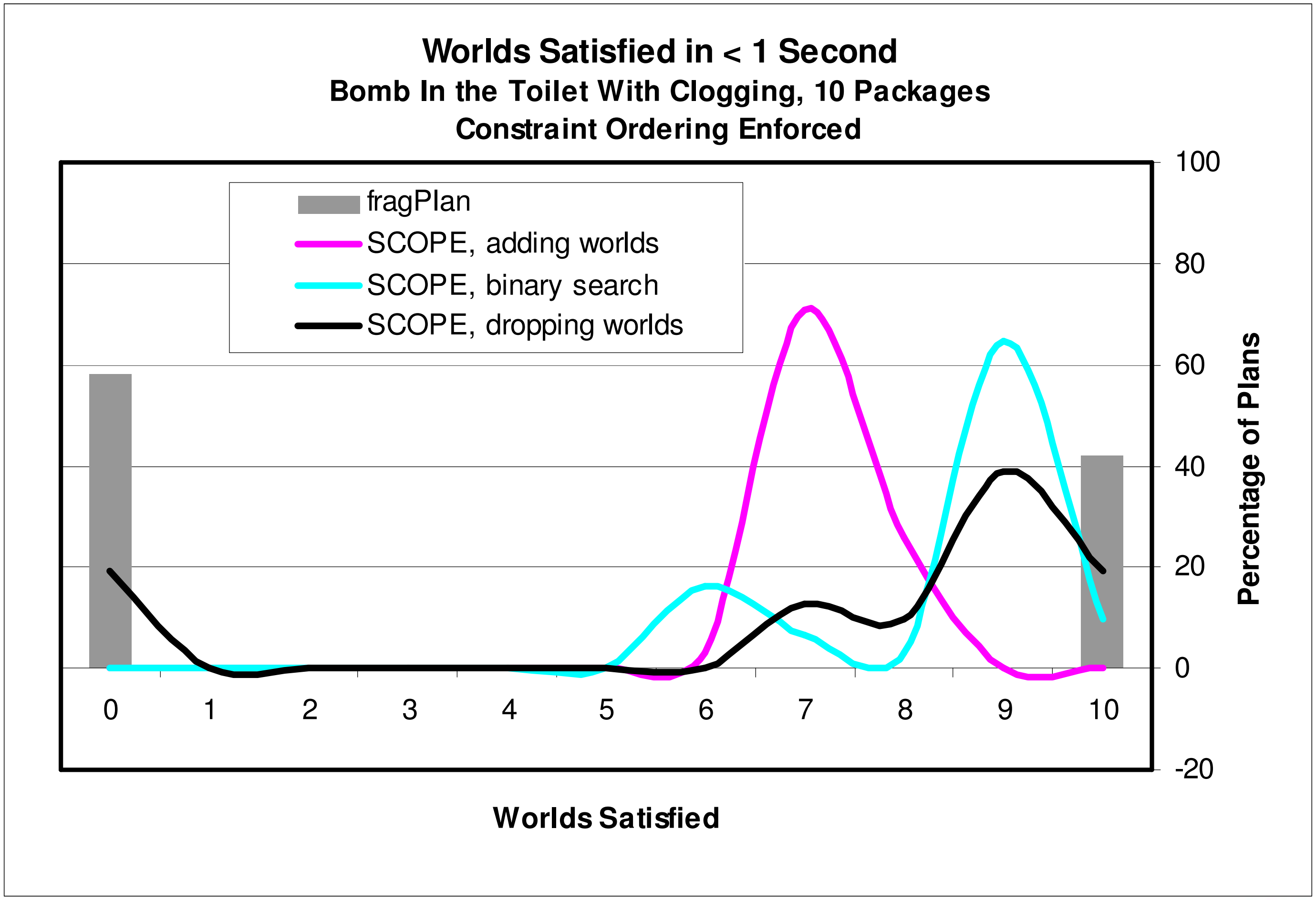
Strategy Performance Versus Time



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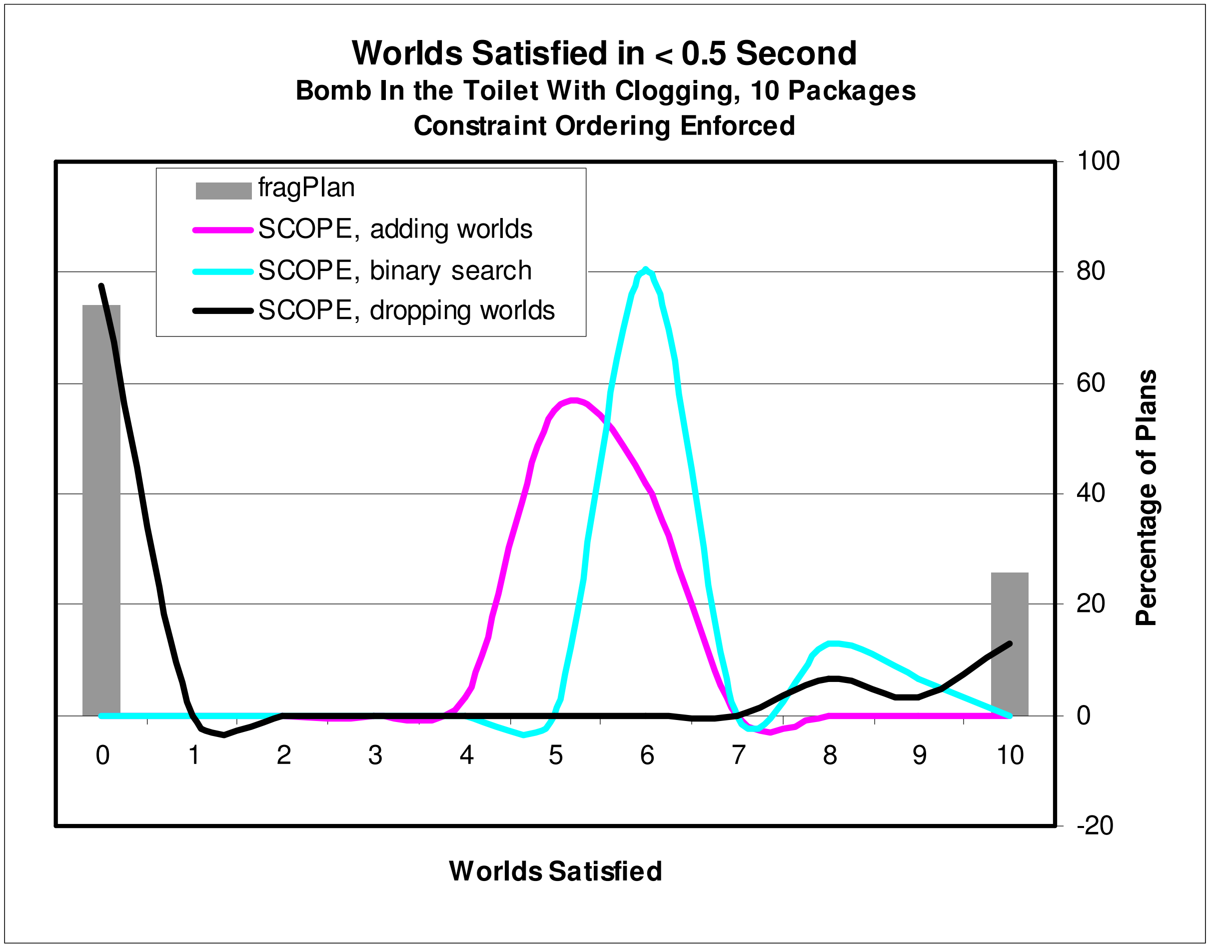
Strategy Performance Versus Time



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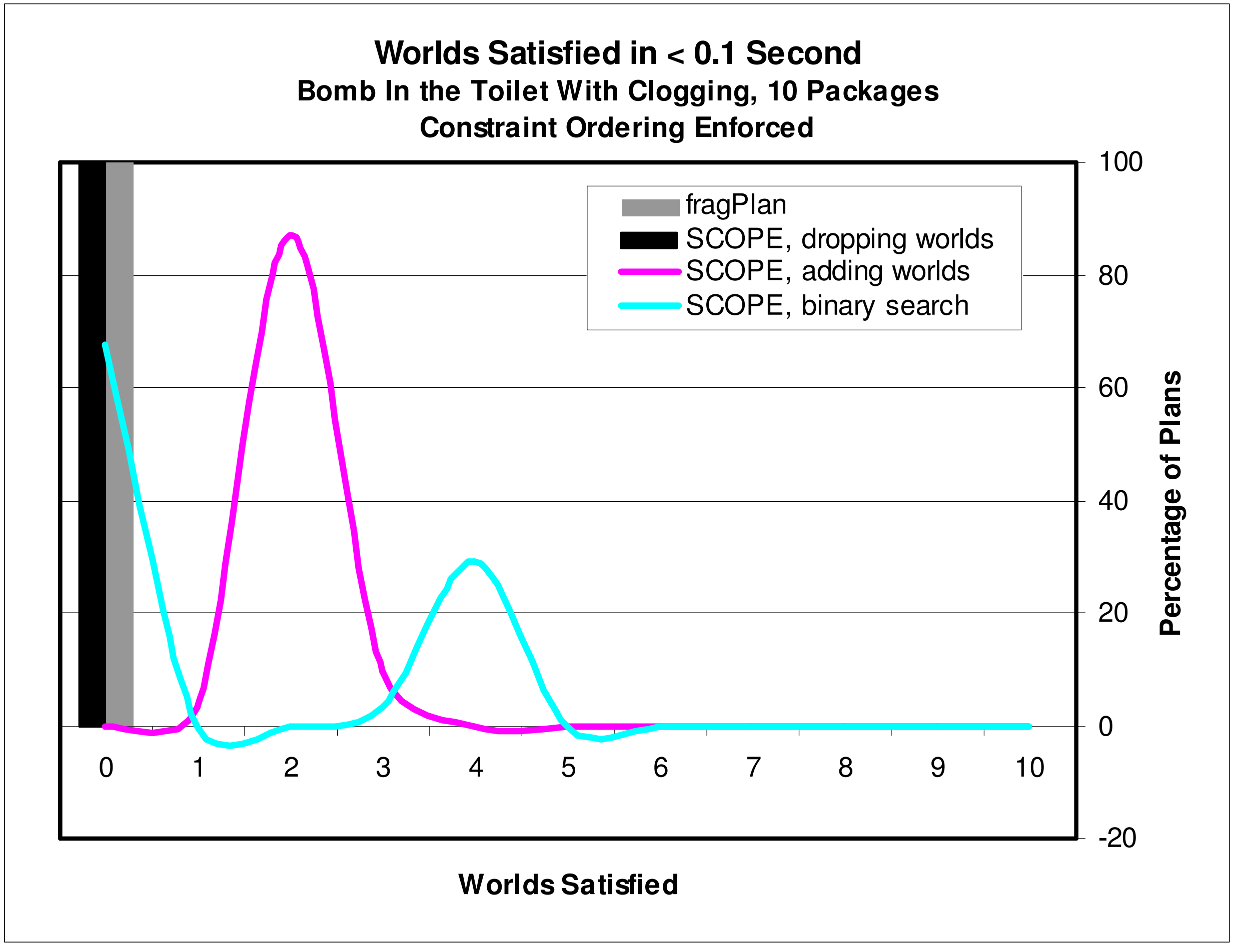
Strategy Performance Versus Time



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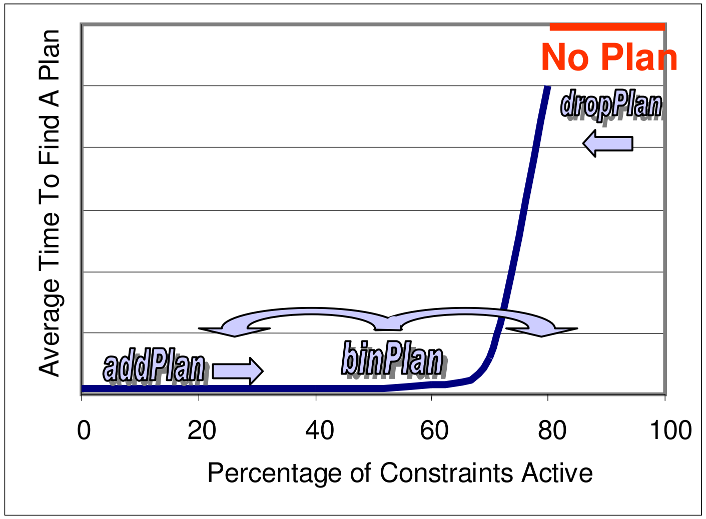
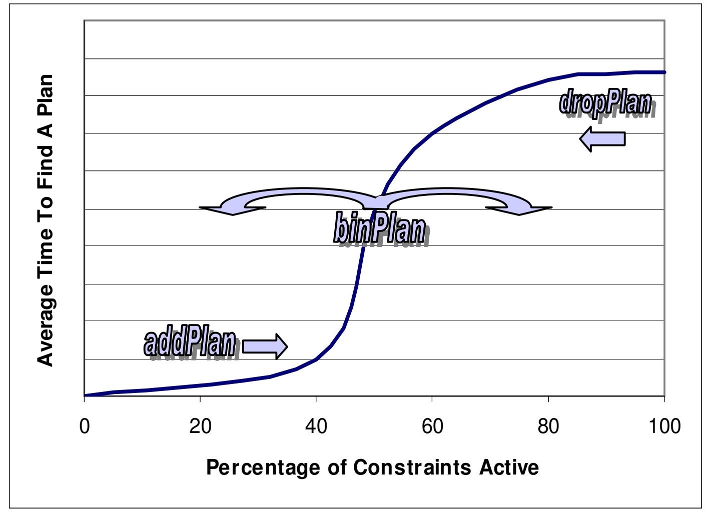
Other Strategies





- dropPlan with difficulty
  - When a plan fails, we can identify the constraints at fault
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- addPlan with sliding
  - If the first plans are easy, move right faster
- Reversal of fortune
  - Start with all constraints and drop, learning difficulty
  - If time runs short, drop all constraints and add least difficult

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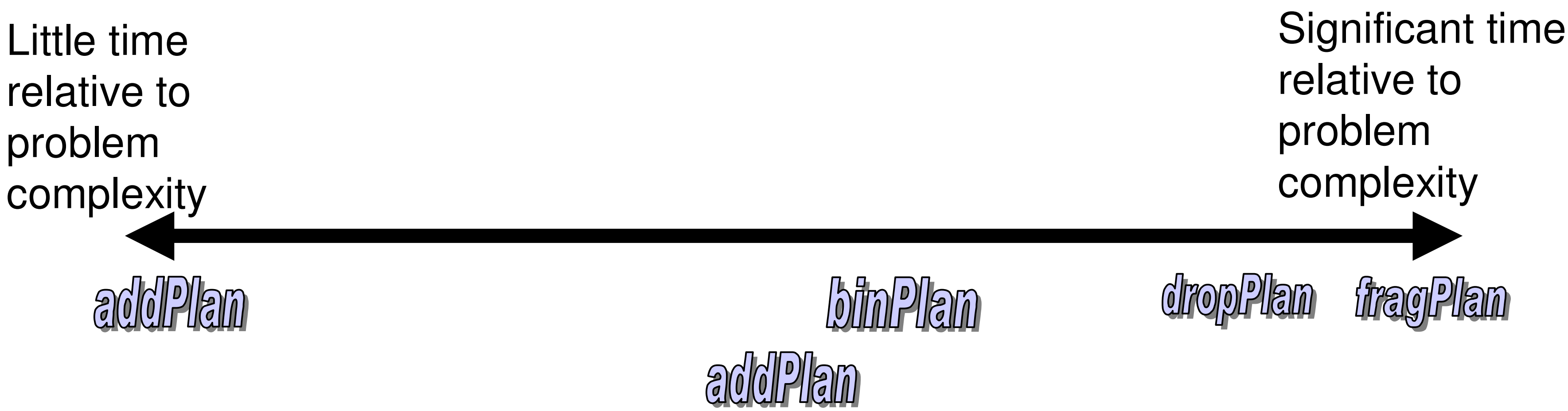
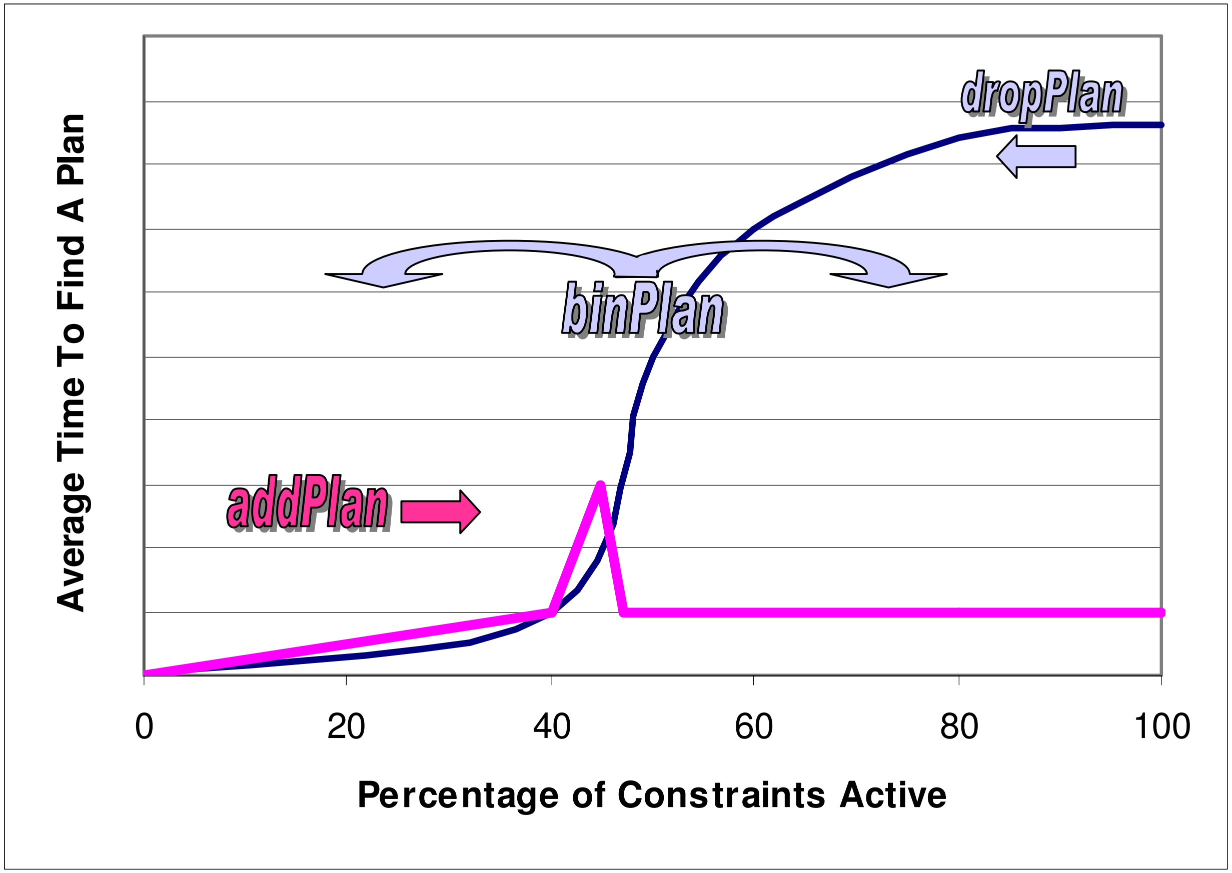
Some Observations On SCOPE

- The best SCOPE strategy varies with time, problem



Some Observations On SCOPE



- addPlan has the advantage of extending an existing plan